11-8-2018

Exploring the Neural Mechanisms of Physics Learning

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EXPLORING THE NEURAL MECHANISMS OF PHYSICS LEARNING

A dissertation submitted in partial fulfillment of

the requirements for the degree of

DOCTOR OF PHILOSOPHY

in

PHYSICS

by

Jessica E. Bartley

2018

To: Dean Michael R. Heithaus
College of Arts, Sciences and Education

This dissertation, written by Jessica E. Bartley, and entitled Exploring the Neural Mechanisms of Physics Learning, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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Date of Defense: November 8, 2018

The dissertation of Jessica E. Bartley is approved.

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Florida International University, 2018

DEDICATION

To those who were there when I needed help,

and to Rafael

ACKNOWLEDGMENTS

This work would not have been possible without funding from the National Science Foundation. The NSF took a chance on a high-risk, high-reward project, allowing us to pursue an ambitious data collection effort to study how learning occurs in the brain. I am extremely grateful for their trust in our ability to carry out this work. I also want to thank and acknowledge the FIU Graduate School Dissertation Year Fellowship for funding my final year of this dissertation.

This project was a tremendous undertaking and an amazing experience. After multiple years of teaching high school physics, I entered FIU with a desire to work on research that could broadly interest and impact instructors and students. I however, had no formal training in neuroscience prior to starting this work. I want to thank the many people in my graduate program who helped me learn the material I needed to master in order to bring my understanding up to the forefront of the field. I also want to thank the scientists and high school physics teachers I met at conferences whose excitement and anticipation about our findings provided the intellectual fuel I needed to keep working.

My deepest gratitude goes to my advisors, Drs. Angela Laird and Eric Brewe, for their mentorship and support. Eric encouraged me to extend my education research interests towards neuroimaging, and I want to thank him for opening this door and for providing mentorship in such a different field than his own. I am also extremely grateful for the investment and trust that Angie has placed in me across these years. She has challenged me at every turn to be a better scientist with her high expectations, enduring support, and unfailing energy. I want to thank her for providing a multitude of resources and opportunities to execute and showcase this work. I would also like to thank my committee members, Drs. Brian Raue, Geoff Potvin, and Matthew Sutherland, for their feedback and contributions towards this work.

Many people helped make this project a reality. I want to extend a special thanks to the FIU undergraduate students who volunteered and participated in this research. This study would not have been possible without these student volunteers. Thanks also to the research coordinators and lab members that assisted with data collection, and to Eli Reyes and Andrea Roman for their expertise and hours of company and conversation in the MRI control room. Thanks to the Physics Education Research Group and the Neuroinformatics and Brain Connectivity Laboratory for their many conversations and input as I endeavored to conduct research that was simultaneously accessible, cutting edge, relevant, and valuable to both fields. Thank you also to my graduate student lab mates and peers for their help in carrying out pioneering science, and for exploring new cities across the globe with me.

On a final personal note, the frustrations of graduate school, especially when compounded with emotional challenges at home, may have been unmanageable it were not for the support of my friends and family. I would like to thank my Grandmother, Jean Leibert, for her love and support, and for showing me how to see the best in any situation. To my friends and family back home, thank you for your constant encouragement, interest, and championship across the years. My love and gratitude goes to Rafael Badui for his unyielding support, kindness, and endless light-heartedness. Rafael helped me prioritize joy and playfulness while completing this work, even and especially through difficult and demanding times. I cannot imagine making it through this marathon without him. Lastly, I want to thank Amy Feineman, Mike Feineman, Karen Raucher, Bob Raucher, and Kay Shafer for always being there for me, through all of it.

The text of this dissertation includes reprints of the following published material:

- Chapter 2: Bartley JE, Boeving ER, Riedel MC, Bottenhorn KL, Salo T, Eickhoff SB, Brewe E, Sutherland MT, Laird AR. Meta-analytic evidence for a core problem solving network across multiple representational domains. Neuroscience and Biobehavioral Reviews, 92 (2018).
- Chapter 5: Brewe E*, Bartley JE*, Riedel, MC, Salo, T, Boeving, ER, Bravo, EI, Odean, R, Nazareth, A Bottenhorn, KL, Laird, RW, Sutherland, MT, Pruden, SM, Laird, AR. Toward a neurobiological basis for understanding learning in University Modeling Instruction physics courses. Frontiers ICT Research Topic on Active Learning: Theoretical Perspectives, Empirical Studies and Design Profiles, 5 (2018).

  *These authors contributed equally to this work (co-first author)

The following material is currently under review and is expected to be published by 2018:

- Chapter 4: Bartley JE, Riedel MC, Salo T, Boeving ER, Bottenhorn KL, Bravo EI, Odean R, Nazareth A, Laird RW, Sutherland MT, Pruden SM, Brewe E, Laird AR (under review). Brain activity links performance in science reasoning with conceptual approach.

As lead author of the papers in Chapter 2 and 4, I was responsible for the majority of the data acquisition, analysis, text, figures, and interpretations. In Chapter 5, Dr. Brewe and I equally contributed to the study: I performed data acquisition, analyses, and contributed text, figures, and interpretations; Dr. Brewe contributed text (especially in the sections on Modeling Instruction and theory), interpretations, and project direction.

NSF REAL DRL-1420627 provided primary funding for these studies. Contributions from co-authors were also partially provided by NIH R01 MH074457, NSF 1631325, NIH R01 DA041353, NIH U01 DA041156, NSF CNS 1532061, NIH K01DA037819, NIH U54MD012393, NIH U24DA039832, NIH R56MH097870, and by FIU Graduate School Dissertation Year Fellowships. All aspects of this study were conducted in accordance with the Social and Behavioral Institutional Review Board of Florida International University, IRB-14-0007. Additional thanks to the FIU Instructional & Research Computing Center (IRCC, http://ircc.fiu.edu) for providing HPC and computing resources that contributed to the research results reported within these papers, and to the Department of Psychology of the University of Miami for providing access to their MRI scanner.

ABSTRACT OF THE DISSERTATION

EXPLORING THE NEURAL MECHANISMS OF PHYSICS LEARNING

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This dissertation presents a series of neuroimaging investigations and achievements that strive to deepen and broaden our understanding of human problem solving and physics learning. Neuroscience conceives of dynamic relationships between behavior, experience, and brain structure and function, but how neural changes enable human learning across classroom instruction remains an open question. At the same time, physics is a challenging area of study in which introductory students regularly struggle to achieve success across university instruction. Research and initiatives in neuroeducation promise a new understanding into the interactions between biology and education, including the neural mechanisms of learning and development. These insights may be particularly useful in understanding how students learn, which is crucial for helping them succeed. Towards this end, we utilize methods in functional magnetic resonance imaging (fMRI), as informed by education theory, research, and practice, to investigate the neural

mechanisms of problem solving and learning in students across semester-long University-level introductory physics learning environments.

In the first study, we review and synthesize the neuroimaging problem solving literature and perform quantitative coordinate-based meta-analysis on 280 problem solving experiments to characterize the common and dissociable brain networks that underlie human problem solving across different representational contexts. Then, we describe the Understanding the Neural Mechanisms of Physics Learning project, which was designed to study functional brain changes associated with learning and problem solving in undergraduate physics students before and after a semester of introductory physics instruction. We present the development, facilitation, and data acquisition for this longitudinal data collection project. We then perform a sequence of fMRI analyses of these data and characterize the first-time observations of brain networks underlying physics problem solving in students after university physics instruction. We measure sustained and sequential brain activity and functional connectivity during physics problem solving, test brain-behavior relationships between accuracy, difficulty, strategy, and conceptualization of physics ideas, and describe differences in student physics-related brain function linked with dissociations in conceptual approach. The implications of these results to inform effective instructional practices are discussed. Then, we consider how classroom learning impacts the development of student brain function by examining changes in physics problem solving-related brain activity in students before and after they completed a semester-long Modeling Instruction physics course. Our results provide the first neurobiological evidence that physics learning environments drive the functional reorganization of large-scale brain networks in physics students.

Through this collection of work, we demonstrate how neuroscience studies of learning can be grounded in educational theory and pedagogy, and provide deep insights into the neural mechanisms by which students learn physics.

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Introduction

1.1 Motivation and Background

Problem solving is an integral construct relevant to understanding how individuals learn and acquire critical thinking skills in STEM (science, technology, engineering, and mathematics). However, the neurobiological mechanisms supporting these STEM skills, particularly in the domain of physics, are understudied and not well understood. Improved understanding of how students process information offers the potential to enhance reasoning and problem solving abilities, learning trajectories, and instructional techniques. Neuroscience conceives of dynamic relationships between behavior, experience, and brain structure and function (Greenough et al., 1987; Kandel et al., 2012; Kolb et al., 2014), but how neural changes enable human learning across classroom instruction remains an open question. Physics in particular is a challenging subject area in which students regularly struggle, as it requires the combined learning and recall of content knowledge and the acquisition of problem solving skills. We do not fully understand the mechanisms for how students develop problem solving skills in physics, nor what neurobiology underlies the different outcomes for students going through university physics instruction. The discipline of cognitive neuroscience provides neuroimaging tools (e.g., functional magnetic resonance imaging, fMRI) that may be useful in characterizing brain function associated with such complex mental operations.

To address these questions, the present NSF-supported project seeks to bridge cognitive neuroscience with education research by using fMRI to determine how learning environments may drive the functional reorganization of large-scale brain networks in physics students. The objective of the project is to characterize the neural correlates of physics problem solving and the influence of learning on knowledge organization and brain function. As such, the overall goal of the study is to delineate the neural correlates of problem solving and learning within the context of university introductory physics. Specifically, the investigations presented in the collection of work aim to: 1) determine the neurobiological substrates supporting human problem solving in general and across multiple content domains, 2) characterize brain function specifically associated with physics-based problem solving using fMRI, and 3) elucidate the influence of physics instruction on such brain activity. What follows in the introduction is a summary of relevant background literature and findings from neuroimaging and education research, as well as a brief overview of the methodological techniques used in the following chapters.

1.1.1 The Neuroscience of Learning

Neuroscience is the study of the relationship between the brain and behavior. A fundamental question that guides much of human neuroscience today concerns how external experiences and brain function exchange influence. Questions such as *how does brain function govern individuals' interactions with or perception of the world, in what* *ways do experiences shape how the brain works,* and *what does the brain have to do with learning* all fall within the purview of cognitive neuroscience. Neuroimaging, which is the non-invasive process of imaging the human brain, has provided powerful tools to help answer these basic questions. Through these techniques we know that learning indeed changes the physical structure of the brain (Draganski et al., 2004; Maguire et al., 2000; Mårtensson et al., 2012; May, 2011; Sakai, 2005; Zatorre et al., 2012). We also know that learning alters brain activity in specific ways by modifying the organization of functional brain networks across experience, training, and environmental changes (Bassett et al., 2015; Lewis et al., 2009; Mason and Just, 2015; Schinazi and Epstein, 2010; Ungerleider et al., 2002).

Neuroimaging learning experiments have traditionally investigated task-related changes in brain function that occur as part of the acquisition of new information or skills (e.g., during information encoding), or those associated with recalled information after training interventions (Karuza et al., 2014). Some common learning neuroimaging paradigms include *sequence learning* in which temporally-varied finger motions or visual/auditory stimuli are memorized, *artificial grammar learning* wherein individuals learn rule-governed letter strings that are generated by novel underlying grammatical structures, or *statistical learning* of probabilistic sequences where judgments are made on pattern structures (Karuza et al., 2014). These and similar investigations have documented various task-specific regional changes in brain function linked with encoding and information recall after training intervals. Many of these studies have focused on short-term or in-scanner interventions (Chein and Schneider, 2005; Delazer et al., 2003; Fletcher, 1999; Mason and Just, 2015; Poldrack, 1998). More recently, researchers have successfully demonstrated proof-of-concept that fMRI can in fact measure longer-term training-related neural developments (Bassett et al., 2015, 2011), including those across classroom learning (Huber et al., 2018; Mackey et al., 2013, 2012; Shaywitz et al., 2004). In one such study, researchers utilized a year-long classroom intervention to assess reading fluency-related brain function in children with reading disabilities, finding that children who underwent remedial educational interventions showed critical developments in the neural circuits supporting reading that were linked to increased success (Shaywitz et al., 2004). Other studies have begun to consider brain function of other school learning-related tasks: one observed individual differences in arithmetic-related brain function correlated with variability in high school mathematical competences (Price et al., 2013); another described specific neural representations as well as patterns in brain function are linked to physics and learning how mechanical systems function (Mason and Just, 2016, 2015). Moreover, recent work has indicated that brain-based measures may be able to predict future success in STEM classroom environments (van Kesteren et al., 2014). These developments open the possibility for neuroscience investigations to be increasingly integrated with classroom measurements and practices (Patten and Campbell, 2011).

Within the context of science learning, problem solving skill development is a critical aspect of success across instruction. In the neuroscience domain, problem solving has been studied in the context of sentence-based inference (Prado et al., 2011), mathematics (Arsalidou and Taylor, 2011), and visuospatial reasoning (Ferrer et al., 2009; Knauff et al., 2002). Findings derived from fMRI suggest the neural substrates supporting problem solving vary across task type (Newman et al., 2011), and that specific cognitive strategies may be responsible for group differences at the neural level (Boghi et al., 2006; Keller and Menon, 2009). In general, fMRI studies have characterized problem solving within particular contexts or content domains, but the neural mechanisms specific to physics problem solving have not been studied and are currently unknown. Likewise, neuroimaging investigations on learning and skill acquisition have only recently started to consider changes in the brain across real-world contexts (Bassett et al., 2015; Mackey et al., 2013; van Kesteren et al., 2014), and the nascent field of neuroeducation hopes to answer how student's brains develop across classroom instruction, thereby informing effective teaching methods (Carew and Magsamen, 2010; Owens and Tanner, 2017).

1.1.2 Physics Learning and Problem Solving: An Education Research Perspective

As described above, many neuroimaging investigations consider learning as the process by which the brain encodes new information to achieve successful and subsequent recall (Bassett et al., 2015; Delazer et al., 2005; Fletcher, 1999; Liu et al., 2014; Smolen et al., 2016; Steinemann et al., 2016; Yonelinas, 2002). Memory formation, and how effectively information can be recalled, is thus often the critically emphasized criterion in neuroimaging studies for establishing whether or not learning has occurred. Education research on learning however, especially within physics or other STEM domains, takes a somewhat different focus. Curriculum and assessments frequently probe for "learning as understanding" (National Research Council, 2000). Within this learning-as-understanding view, the ability to access content knowledge is essential but not sufficient for successful learning. Physics in particular is a domain that emphasizes the ability to think and solve problems, and therefore physics learning obligates students to acquire knowledge that is both *accessible* and *useable* (Redish, 2003; Sabella and Redish, 2007). That is, students who memorize physics facts without understanding their meaning or context usually struggle to apply their knowledge to solve problems. Learning how to select and then apply content knowledge via critical thinking is necessary in learning how to do physics.

Viewpoints on how students build knowledge and develop critical thinking skills vary. One theme in education research focuses on how students apply physics concepts within reasoning. When students enter a physics classroom, they already possess a wealth of prior knowledge, skills, and ideas that help them construct new understanding (McDermott and Redish, 1999; Thacker, 2003; Tuminaro and Redish, 2007) . However, if their preconceptions conflict with what is being taught in the class, then students may struggle to learn and apply new concepts within reasoning (McDermott, 1991). To some teachers and education researchers, concept learning necessitates first identifying student's conflicting conceptions and then helping them change incorrect conceptions to correct ones (Chi et al., 1994; Dykstra et al., 1992; Posner et al., 1982; Slotta et al., 1995). Another view considers physics thinking as being made up of more short-term, contextually primed knowledge pieces referred to as "phenomenological primitives" or "resources," that students activate when solving problems (diSessa, 1993; Hammer, 1996a; Hammer et al., 2005; Redish, 2003). Under the resources view, concept learning involves helping students assemble and appropriately link their primed resources with physical laws to facilitate successful problem solving. The resources view may be a particularly useful framework within which to consider physics learning and guide instructional practice, insofar as evidence suggests students can have very different responses to similar questions depending on how the question is framed (Tuminaro and Redish, 2007).

Thus, effective physics instruction needs to provide students with relevant content knowledge required to solve problems, and also help them learn to organize that knowledge in ways that facilitate retrieval and reasoning (National Research Council, 2000). When instruction fails to do this students may exit their classes with large and unmanageable knowledge bases made up of a conglomeration of knowledge pieces that include disconnected concepts, definitions, equations, and/or laws (e.g., velocity is a vector quantity, $F = ma$, energy is conserved). On the other hand, when physics instruction is successful, students learn to build connections between related knowledge elements, thus forming coherent and organized knowledge structures that they can use to construct models to explain physical phenomena and solve problems (Redish, 1994).

Given this framework of knowledge and learning, what instructional practices best support successful physics learning? Research in science education finds physics students receiving instruction in active-learning environments, as compared to those in courses that engage students primarily as passive listeners during class, regularly demonstrate increased conceptual understanding, perform better on course examinations, and are more likely to pass introductory classes (Freeman et al., 2014; Hake, 1998). Physics courses that use active engagement techniques can take a multitude of formats. Active-learning instructional methods dedicate class time to explicitly actively engaging students with the course material and can include experimentation (Waldrop et al., 2015), argumentation (Jimenez-Aleixandre et al., 2000), peer-to-peer instruction and other formative assessment methods (Crouch and Mazur, 2001; Moss and Brookhart, 2009), scientific inquiry (Bybee et al., 2000), and/or cooperative learning (Frey et al., 2009). One active-learning format class currently implemented at Florida International University (FIU) is called Modeling Instruction. Modeling Instruction is a theory-driven curriculum intervention and pedagogy in physics in which students participate in active-learning studio classrooms where they develop, test, and verify physics models through inquiry-based collaborative group activities (Brewe, 2008). Similar to the results observed in other active-learning environments, FIU Modeling Instruction students show greater positive shifts in conceptual physics reasoning skills across instruction, relative to their lecture instruction peers (Brewe et al., 2010b). Based on the theory that science is built upon the continual practice of developing, verifying, and revising models, Modeling Instruction teaches students to build, test, and revise physics models through inquiry-based collaborative group activities. This instructional method is thought to explicitly help students develop organized physics knowledge structures that they can use to successfully solve problems. The current project, described in more detail in §1.1.3 Building a Bridge Between Education and Cognitive Neuroscience and §3.1 Project Overview, collects data from students in Modeling Instruction as well as Lecture Instructions classrooms at Florida International University.

1.1.3 Building a Bridge Between Education and Cognitive Neuroscience

Education research examines and incorporates student's actions, concerns, and performances to assess and build educational practices that support learning. If student's needs are not being appropriately addressed then education research can help structure better pedagogies or learning environments to improve educational outcomes. However, such research is unable to investigate important foundational features of learning such as how content knowledge and critical thinking skills are supported in the brain. Neuroscience, on the other hand, while having supplied valuable insight into the various mechanisms that underlie learning-related cognition, has by in large produced investigations that insufficiently consider student learning from an integrative social, cognitive, and affective perspective. If left unconnected with the findings and values of educational research and instructional practice, neuroscientific investigations of learning will remain inadequately adapted to relate essential facets of student's experiences with strategies that impact or impede learning.

To bridge this divide, neuroeducation is emerging as a cross-disciplinary field that applies neuroscience methods and techniques to consider learning from a perspective informed by education theory, research, and practice. Neuroeducation research and initiatives promise a new understanding into the interactions between biology and education, including the neural mechanisms of learning and development (Ansari and Coch, 2006; Coch and Ansari, 2009; Goswami, 2004; Mason, 2009). Grounding neuroscience studies of learning in educational theory and pedagogy can edify the extent to which neurobiological changes are influenced or supported by intrapersonal and environmental factors. We can thus work to clarify, define, and create new models of learning that provide insight into the underpinnings of student learning difficulties and how to prevent them (Butterworth et al., 2011; Kaufmann et al., 2009; Pera, 2014). Proof of concept has already been established demonstrating educational related changes in the brain can be measured by fMRI (Mackey et al., 2013; Shaywitz et al., 2004; van Kesteren et al., 2014). Researchers are also beginning to call for further studies that combine fMRI data and behavioral measures to investigate human learning (Karuza et al., 2014), which can be applied to investigating student concept formation across classroom instruction. At the same time, research institutions are beginning to develop and implement models for longitudinal neuroeducational studies which may provide distinct advantages for detecting the time-dependent mechanisms by which the brain acquires new knowledge across long-term learning (Koizumi, 2011).

Neuroeducation remains a developing field wherein basic research must first be established before wider educational tools can be refined for use in classrooms. Despite the promises of this new field of research, some argue that studying the brain may never yield the eventual curricular developments and insights that neuroeducation researchers hope may one day aid teachers and benefit students (Bruer, 2006, 1997). It has also been wisely pointed out that educators know much more about which learning techniques work in their classrooms than neuroscientists do, and we must be careful to resist the urge to treat the results of brain scans as asserting more consequence or authority than behavioral observations of student's experiences and successes (Coch and Ansari, 2009). The collected works that make up this dissertation are aligned with the perspective that neuroeducation research must be integrated with, and not a proxy for, educational and qualitative research perspectives and techniques, and thus must share a common set of concerns and values that place students in the forefront.

In answer to these calls, the four achievements and investigations presented in this collected work are part of a larger neuroeducation project entitled *Exploring the Neural*

Mechanisms of Physics Learning. Designed around the epistemology and theory behind Modeling Instruction, the larger project seeks to gather and assess evidence of human learning and knowledge organization across classroom instruction, as measured by longitudinal fMRI of student brain activity across semester-long University Physics learning experiences. By investigating the role instructional settings play in influencing neural organization, these sets of studies have the potential to provide deep insight into the ways in which students learn physics. While the larger *Exploring the Neural Mechanisms of Physics Learning* project is ongoing, the present collection of work presents the development of and initial studies that make up this ambitious neuroeducation project. With a focus on the domain of physics, we thus take up the challenge of establishing a foundational knowledge on the neurobiology of classroom learning in attempt to connect findings of neural mechanisms with those of effective classroom practices. Through this collection of work, we aspire to demonstrate the value of these investigations and thus guide future neuroeducation research directions driven by these common goals.

1.2 A Primer on Brain Function and Neuroimaging

Neuroscience is a broad field encompassing multiple subdisciplines, of which systems-level human functional neuroimaging is just one. The studies presented in this collection use the techniques and language of neuroimaging. However, the broader content and motivation for these investigations cross boundaries across multiple disciplines including education, biology, and psychology. Thus, as an aid to readers who may not be familiar with neurobiology or the terminology, techniques, and major findings of neuroimaging relevant to this work, a brief primer on brain function and neuroimaging methodology and analysis are provided below.

1.2.1 Neuronal Foundations

Two types of cells make up the brain: neurons and glia. Neurons send and receive electrical signals, called action potentials, across vast cellular networks by inducing changes in neuronal membrane polarity characterized by a quick depolarization across the cell boundary followed by a longer period of repolarization and refractory hyperpolarization that then level out to baseline (Kandel et al., 2013). These signals make up the basis of how the brain receives, transmits, and analyzes information. Glial cells support the overall function of this system of neuron-to-neuron communication. A single long projection from a neuron's cell body, called the axon, sends action potentials, while numerous shorter projections from the cell body, called dendrites, receive signals from neighboring axons (Kandel et al., 2013). To increases the speed by which action potentials travel across neurons, axons are surrounded by insulating sheaths of myelin, which is a fatty substance formed by glia. Myelinated axons are known as "white matter" and their dendritic and neuron cell body counterparts are known as "gray matter". Cognition is said to occur within the gray matter where signals are received and initiated, thus we focus all analyses presented in this collection of work within gray matter areas of the brain.

When an individual experiences sensory stimuli or engages in motor, cognitive, emotional, or other processes, action potentials are fired across sets of neurons in specific areas of the brain. In order for an action potential to fire, ATP is consumed locally in the region. This process requires oxygen to be drawn from the blood in surrounding capillaries. After oxygen is consumed, blood flow to the region increases so as to replenish the resulting regional lack of oxygenated blood (Huettel et al., 2009a). The displacement of deoxygenated hemoglobin with oxygenated hemoglobin, two substances in the blood that have slightly different magnetic properties, form the basis for how we are able to trace where cognition occurs in the brain (Huettel et al., 2009a).

1.2.2 Functional Magnetic Resonance Imaging

Magnetic resonance imaging (MRI), developed in the early 1970s and based on the principle of nuclear magnetic resonance, is a non-invasive technique used to image the body (Huettel et al., 2009b). Different biological substances have different magnetic susceptibilities and therefore behave differently when placed in a strong magnetic field. This effect allows for contrast in signal intensities between various soft tissues and fluid types in MRI images. When a human is placed in a large static magnetic field (3T is a common MRI field strength), nuclei magnetic moments within the body align with and precess about the axis of the external field. The effect produces a net bulk nuclear magnetization of $\boldsymbol{M} = \boldsymbol{M}_z + \boldsymbol{M}_{xy}$, where $\boldsymbol{M}_z$ is in the direction of the external field and $\boldsymbol{M}_{xy}$ is transverse to the external field (Huettel et al., 2009c). A radio frequency (RF) pulse is then tuned to the Larmor frequency (i.e., the precessional rate) and applied to the tissue along the transverse direction. The RF pulse causes nuclei spins to flip into their higher energy, antiparallel states. This induces precessional phase coherence across nuclei magnetic moments and results in an increased $\boldsymbol{M}_{xy}$ and decreased $\boldsymbol{M}_z$. After the pulse is removed, spins return to their lower energy states parallel to the longitudinal static field as $M_z - M_0 \propto -e^{-t/T_1}$ recovers and $M_{xy} \propto e^{t/T_2}$ decays (Kuperman, 2014). Critically, the decay rates for the longitudinal, T_1, and transverse, T_2, processes depend on the tissue type. From Faraday's Law, the time-varying magnetization induces a voltage in the radio frequency coils that surround the person within the scanner. These voltages are known as the magnetic resonance (MR) signal. Careful tuning and sequencing of RF pulses via magnetic field gradients constrain precessional frequencies to become spatially dependent, which allows for localization of the MR signal. Echo-planar imaging is one such technique, and used here in the dissertation, to collect a fast sequence of spatially dependent two-dimensional MR images by rapidly changing magnetic gradients following the RF pulse from the head coil. The image of these transverse magnetizations linked to each spatial location is then reconstructed via inverse Fourier transform of the MR signal, $S(k) \propto \int M_{xy} e^{ikr} dV$, where k is the spatial frequency of the gradient fields and integration is performed across the volume being imaged (Kuperman, 2014).

The images produced as a result of MRI are black and white spatial volumes in which volumetric pixels, or "voxels", are shaded according to the mean signal intensity detected at that spatial location. Structural MRI images are typically high-resolution (~1x1x1mm^3 voxel) volumes whereas functional MRI images are lower resolution (~3x3x3mm^3 voxel). Functional magnetic resonance imaging utilizes rapid pulse sequences that acquire a full volume every "repetition time", or TR, which is the time interval between successive RF pulses. The rapid collection of fMRI images results in a 4D (3 spatial x 1 time) data set. Within a single voxel, the collection of sequential signal intensities across time is known as the voxel's "time series". These time series make up the fundamental unit of analysis in fMRI data. Researchers are able to determine how the brain is engaged during cognition via the statistical analysis of time series that represent how specific brain areas function across time. In general, the result of such analyses is a full brain volume in which a single statistic, representing the result of one or multiple tests, is assigned to each voxel. Typically, these 3D images are depicted as sequential 2D slices that highlight different "levels" or heights of the full brain volume.

1.2.1.1 fMRI Experimental Setup

When a person participates in a fMRI experiment they agree to have one or more MRI scans performed of their brain. As part of this process, the individual lies supine in the MRI scanner while their head rests within a radio frequency head coil that emits RF pulses and collects data on their brain function. Soft pads are placed around the participant's head to reduce head motion. Participants are also provided with hearing protection to reduce scanner noise, a fiber optic button press with which to answer questions and respond to stimuli during the scan, and a signaling device in case of emergencies if they need to exit the scanner. Before the start of each scan, a display screen is set up at the end of the MRI scanner's bore. Questions and stimuli are projected onto this screen from a computer located in the MRI control room, and participants can view this display screen via a mirror that has been mounted at an angle to the top of the head coil. During a functional MRI run (e.g., a period in which the MRI scanner is collecting data), the person is asked to engage in cognitive tasks presented on the view screen or lie quietly while the MRI collects data on their brain function. "Task-based" fMRI refers to runs in which the participant completes cognitive tasks. "Resting-state" fMRI refers to the runs in which functional data is collected on a participant's brain function, but the participant is not provided any specific task to complete while in the scanner. Such scans are used to collect data on the spontaneous neural fluctuations associated with this task-free state (Biswal et al., 1995). Between runs the experimenter in the MRI control room can provide feedback or instructions on upcoming tasks via a microphone connected to the participant's headphones.

The stimuli presented during task-based fMRI are usually presented as either a "block" design or an "event" design. The stimuli, which could be individual questions or tasks, are referred to as "trials", and the trial types (e.g., memory problems vs. physics problems) are known as a "conditions". In block design tasks, participants complete multiple trials of the same condition for some time interval (e.g., a "block", usually ~10-30 seconds in length; Huettel et al., 2009d). Blocks are usually followed by short periods of "rest" in which central fixation cross appears on the screen. This interleaved block/rest procedure allows the experimenter to determine when a MR signal corresponds to a specific conditions or when it relates to baseline task-free brain function. During the analysis of fMRI data (see §1.2.2.3 fMRI Preprocessing and Analysis) blocks of different conditions are "contrasted" so that brain activity associated with only specific cognitive functions can effectively be isolated from the overall task-free signal. Event related designs are similar to block designs, but individual trials are instead either continually presented across the run (for "fast" event related design) or are interspersed across longer periods of rest ("slow" event related designs). The application and development of these design types in the contexts of the current project are discussed in more detail in §3.2 Task Development.

1.2.2.2 The Blood Oxygenation Dependent Signal

As was introduced above, oxygenated and deoxygenated hemoglobin (HB) possess different magnetic properties that allow for their contrast via MRI. Oxygenated HB is relatively more diamagnetic while deoxygenated HB is more paramagnetic, and the resulting contrast between their transverse decay curves is known as the Blood Oxygenation Level Dependent (BOLD) contrast (Huettel et al., 2009a). When an action potential is fired across neurons, oxygen is initially drawn away from regional capillaries, followed by an increase in oxygenated blood flow to the area. This process is known as the brain's hemodynamic response (HDR). In fMRI, we measure the brain's HDR via the BOLD contrast as the change in MR signal following local neuronal activity. Measurements of the BOLD signal provide us with an indirect measure of neuronal activity following cognition.

1.2.2.3 fMRI Preprocessing and Analysis

At 3T field strength, the range of BOLD signal accounts for approximately 2-5% change in the overall observed signal (Poldrack et al., 2011). Thus, BOLD fMRI is particularly sensitive to sources of noise including head motion, physiological noise, thermal and equipment noise, and magnetic susceptibility artifacts. Preprocessing of fMRI data must be performed before statistical analyses are carried out to clean and diminish the effect of factors that distort or otherwise obscure the BOLD signal. In addition to reducing such undesired variability from the data, preprocessing also prepares fMRI data for statistical comparison across individuals so that group-level inferences can be made. Determining and advancing best practices in fMRI preprocessing is an active field of research and we will not review all techniques for cleaning and processing fMRI data here. Briefly, some components of this process include motion correction to reduce the effects of in-scanner head motion, spatial interpolation to estimate signal in spatial locations that were not sampled during the scan, co-registration to link brain regions across time-indexed functional volumes and to high-resolution anatomical markers, temporal filtering to remove low frequency equipment noise and frequencies associated with physiological (e.g., heart rate and respiration) processes, "prewhitening" to remove task-uncorrelated noise and decrease the effects of temporal autocorrelation in time series, spatial smoothing to improve statistical power and increase signal to noise, and spatial normalization to transform functional images from subject native space to a standardized brain space (commonly used templates include the Montreal Neurological Institute (MNI) and Talairach standardized brain spaces) to allow for comparison of subject-level fMRI results across individuals (Poldrack et al., 2011).

After preprocessing, statistical analyses across time series and study participants are then performed. Many methods for analyzing fMRI data exist. However, the most commonly implemented analyses, and the ones presented in this body of work, all rely on multileveled modeling techniques. Typically, after fMRI data have undergone cleaning and pre-processing, analyses are first performed at the so-called "subject-level" in which parallel analyses are conducted on time series data for each study participant at each voxel. The results of these subject-specific results are then brought into the "group-level" for comparison across individuals. That is, participant-specific analyses are contrasted or otherwise mathematically compiled across all individuals participating in the study so that generalization can be made across a larger population. All neuroimaging analyses presented in this dissertation use a hierarchical general linear modeling (GLM) approach.

The GLM is a statistical linear modeling technique commonly used in fMRI data analysis that incorporates multiple analysis types including correlation, *t*-tests, multiple linear regression, and analysis of variance (ANOVA) (Beckmann et al., 2003; Monti, 2011; Poldrack et al., 2011). The GLM relates a continuous dependent variable with one or more independent categorical and/or continuous variables called "regressors" by performing least squares regression. The multiple linear regression form of the GLM is $\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{\epsilon}$, where $\boldsymbol{Y}$ is a vector of length N representing the dependent variable (the data), $\boldsymbol{X}$ is the $N \times M$ matrix of regressors, called the "design matrix", of which each column corresponds to a single regressor X_i , $\boldsymbol{\beta} = [\beta_0, \beta_1, \beta_2, \dots, \beta_M]'$ is a vector representing the parameter coefficients for each regressor, and $\boldsymbol{\epsilon}$ is the the random vector of errors of length N. The assumptions of the GLM are that any two elements in the error vector are uncorrelated, $Cor(\epsilon_i, \epsilon_j) = 0$, and that the errors follow a multivariate normal distribution with mean 0 and variance σ^2, $\boldsymbol{\epsilon} \sim N(0, \sigma^2 \boldsymbol{I})$, where $\boldsymbol{I}$ is the $N \times N$ identity matrix. Provided $\boldsymbol{X'X}$ is invertible (e.g., no column in $\boldsymbol{X}$ is a linear combination of any other column in $\boldsymbol{X}$), minimizing the sum-of-squares of the residuals gives a vector of parameter estimates. Hypothesis tests can then be performed on linear combinations, called "contrasts", $\boldsymbol{c\beta} = 0$, of the parameter estimates. The form of $\boldsymbol{c}$ determines what kind of test is being performed (e.g., a one-sample *t*-test, two-sample *t*-test, paired *t*-test, two-way ANOVA, and so on). In each case, the test statistic is given by $t = \frac{\boldsymbol{c\hat{\beta}}}{\sqrt{\boldsymbol{c}(\boldsymbol{X'X})^{-1}\boldsymbol{c}'\hat{\sigma}^2}}$.

If desired, these t scores can be transformed into standardized z values (Poldrack et al., 2011).

In subject-level fMRI GLM analyses, $\boldsymbol{Y}$ represents a single voxel time series and each X_i represents an explanatory variable that purportedly accounts for some portion of the variance contained within the time series data. For example, in block design experiments, conditions are modeled as boxcar functions that indicate the onset and offset of each block. These condition regressors make up the columns in the design matrix $\boldsymbol{X}$. As another example, in resting-state designs in which $\boldsymbol{Y}$ cannot be modeled via some task condition, the time series from other voxels or regions of interest are used as the explanatory variable. Analyses of this type are referred to as "functional connectivity" analyses because they measure temporally correlated changes in the BOLD signal across distributed brain regions. So-called "nuisance" regressors such as head motion parameters, respiration rate, or other task-unrelated variables that may influence signals can also be included as regressors in the design matrix at the subject-level. In this way, a GLM is performed at each voxel and for each participant in the study. If more than one functional run was acquired from the same individual, and GLMs of each run were performed separately, then voxel-wise one-sample t-tests are performed to average the parameter estimates across each run. The result of these subject-level analyses is a 3D volume for each participant in the study in which each voxel contains a set of beta weights that correspond to the regressors of interest.

The results of these subject-level analyses are then carried into one or more higher-level statistical analyses at the group-level. In group-level analyses, $\boldsymbol{Y}$ represents the vector of parameter estimates within a single voxel across all participants in the study. That is, the input data might be $\boldsymbol{Y} = [Y_{Sub.1,Vox.j}, Y_{Sub.2,Vox.j}, \dots, Y_{Sub.N,Vox.j}]'$. In this level of analysis, each X_i represents an explanatory variable that models factors such as participant group, scanning session, or other measures of interest. Voxel-wise statistical tests are conducted to contrast the resultant subject-level beta maps across the factors of interest (e.g., Group 1 vs. Group 2, Session 1 vs. Session 2, or so on). The result of a group-level analysis is a single 3D volume wherein each voxel contains a single statistic, typically either a *z* or *t* score, which corresponds to the result of the statistical test that was run. Because a very large number of hypothesis tests are performed at the group-level (one for each voxel in the brain), correction for multiple comparisons must be performed to reduce false positives. Correction for multiple comparisons is usually accomplished by first applying a strict uncorrected "cluster defining threshold" to the statistic at each voxel, usually $P < 0.001$. Then "cluster extent thresholding" is performed to determine what size clusters constitute significant activations, which is typically familywise error corrected at a level of $P < 0.05$ (Eklund et al., 2016; Mumford et al., 2016).

1.2.3 Brain Function at the Macroscopic Level

The human brain is made up of distinct functional regions. The primary objective of neuroimaging is to map how brain regions are linked with particular functional roles. The four primary divisions of the cerebral cortex, which is the heavily folded outer layer of the brain, are the frontal, parietal, occipital, and temporal lobes. The frontal lobe, in the anterior portion of the cortex, is linked to diverse cognitive functions including executive functions such as cognitive control, reasoning, planning, memory, learning, and those processes guiding goal-directed actions (Donoso et al., 2014; Goldman-Rakic, 1987; Miller, 2000; Miller and Cohen, 2001; Siddiqui et al., 2008). The parietal lobe, located in the posterior and superior portion of the cortex, is responsible for a number of operations including somatic, spatial, and attentional processing, as well as the analysis of visual information (Behrmann et al., 2004; Behrmann and Shomstein, 2009; Goldberg, 2001; Patel et al., 2009). Located beneath the lateral fissure in both hemispheres, the temporal lobe's primary function is processing auditory sounds, including speech and language comprehension (Abhang et al., 2016; Baars et al., 2010). However, this region is also linked to a diverse set of cognitive functions including social processing, long-term memory formation, facial recognition, emotion processing, and understanding written language, among others (Abhang et al., 2016; Baars et al., 2010; Dharani and Dharani, 2015; Olson et al., 2013). The occipital cortex, which encompasses the posterior and inferior part of the cortex, is primarily responsible for vision, with occipital cortex sub-divisions attributed to primary visual areas (e.g., those responsible for the perception of color, motion, and shape), as well as areas engaged in higher-level visual integration and interpretation, as influenced by expectation and attention (Galetta, 2017). The structures that lie immediately underneath the cortex are collectively known as the limbic system. These interconnected sets of regions are responsible for multiple behaviors and functions including autonomic bodily processes, and those associated with emotion, learning, and memory (Isaacson, 2001). Each of the above described general brain regions contains sub-areas that have specific names and that are implicated in various cognitive functions.

1.2.4 Functional Brain Networks

The human brain constitutes a complex interconnected system in which a multitude of networks continually and dynamically processes and relay information across sets of brain regions. Naïvely, early neuroscientists conceived of brain function as primarily described by simple one-to-one mappings between brain areas and specific behaviors or functions (Kandel et al., 2012). It has been widely demonstrated that this is not the case. While some regions do appear to show various degrees of functional specialization (i.e., the primary visual cortex, the motor cortex, or the fusiform face area, to name a few), the vast majority of brain function appears to instead rely on distributed processing wherein large constellations of brain areas, colloquially referred to as networks, operate in tandem of achieve specific aims. Individual regions are often implicated by multiple cognitive functions, and areas that are activated within one functional network can also be activated within other, functionally distinct networks. Indeed, some brain regions appear to be particularly important "nodes" that allow for information exchanges across networks (Buckner et al., 2009; Leech and Sharp, 2014). Moreover, advances in neuroimaging have begun to consider these processes within a "systems-level" model of brain function in which multiple temporally independent, and in some cases spatially overlapping, brain networks continually interact to support brain function during task and at rest (Bassett and Gazzaniga, 2011; Sporns, 2011). Three major networks known to be involved in a range of human brain function are the central executive network (Bressler and Menon, 2010; Seeley et al., 2007), the default mode network (Raichle et al., 2001), and the salience network (Menon, 2015; Seeley et al., 2007). Other commonly observed networks are the dorsal attention network and networks associated with motor control, visual, and auditory processes (Damoiseaux et al., 2006; Laird et al., 2011; Smith et al., 2009; van den Heuvel and Hulshoff Pol, 2010). Hierarchical fractionations within these networks have also been observed (Laird et al., 2017; Leech et al., 2011). Overall, and depending on the cognitive state of the individual, these whole-brain networks can be highly integrated or segregated, and their interactions dynamically vary over time (Bassett et al., 2015; Fransson et al., 2018; Sporns, 2013).

1.3 Dissertation Structure

This dissertation is the compilation of four independent achievements. First, I present a quantitative meta-analysis of 280 problem-solving experiments from the cognitive neuroimaging literature. The work provides a comprehensive set of observations on the brain networks underlying human problem solving across and within specific content domains, thus laying the foundations on which to interpret results from physics problem-solving specific neuroimaging experiments that follow. The meta-analysis was published in the journal Neuroscience and Biobehavioral Reviews (Bartley et al., 2018).

The bulk of my graduate work focused on data acquisition for a broad, NSF-funded neuroeducation study entitled *Exploring the Neural Mechanisms of Physics Learning*. Thus, I next present a summary of the development, piloting, and acquisition of a large set of longitudinal neuroimaging and behavioral neuroeducation data. I present the creation of three novel fMRI paradigms that probe specific psychological constructs linked with problem solving (e.g., semantic memory and reasoning), outline task parameters, scan procedures, and describe a series of data acquisitions that were carried out over the course of three years, as called for within the larger data collection project. I provide an overview of the recruitment and scanning efforts of this project resulting in a large fMRI data sets from 121 undergraduate students, before and after a semester of introductory physics (PHY 2048) at Florida International University, who completed 229 MRI scans accounting for more than 340 scan hours.

Third, I present the first of a series of manuscripts prepared from these data that focused on measuring and characterizing the brain networks linked with physics problem-solving in college-level introductory students immediately after the completion of a semester of university physics instruction. This study presents first-time observations of physics problem solving-related brain networks in students and serves to elucidate how the underlying neural mechanisms of physics problem-solving are associated with strategy and the neurobiological basis of differences in physics conceptualizations during reasoning. This manuscript is currently under review and is expected to be published by the end of 2018.

The fourth and final achievement presents an fMRI investigation that focuses on physics reasoning-related brain networks in students as resulting from a semester of university physics instruction. The theoretical motivation of the wider *Exploring the Neural Mechanisms of Physics Learning* project seeks to investigate how students develop mental models across physics instruction, thus this investigation focused all analyses on students who completed physics Modeling Instruction. The study explores pre- to post-instruction changes in functional brain networks across Modeling Instruction. The paper was published in a special edition of *Frontiers Research Topics* for *Active Learning:*

Theoretical Perspectives, Empirical Studies and Design Profiles (Brewe and Bartley et al., 2018).

The combined outcomes of the analyses presented in this work are a set of statistical parametric images that describe the first ever observations of: (1) the brain networks associated with domain-specific as well as content-general problem solving, (2) the neural substrates of physics problem solving in introductory physics students and, (3) the brain-based impact of real-world educational experience at the university level. Future work and additional analyses associated with the project are beyond the scope of this dissertation. Preparations of these studies are discussed in the Conclusions and Future Work chapter.

Chapter 2

Meta-Analytic Evidence for a Core Problem Solving Network Across Multiple Representational Domains

2.1 Abstract

Problem solving is a complex skill engaging multi-stepped reasoning processes to find unknown solutions. The breadth of real-world contexts requiring problem solving is mirrored by a similarly broad, yet unfocused neuroimaging literature, and the domain-general or context-specific brain networks associated with problem solving are not well understood. To more fully characterize those brain networks, we performed activation likelihood estimation meta-analysis on 280 neuroimaging problem solving experiments reporting 3,166 foci from 1,919 individuals across 131 papers. The general map of problem solving revealed broad fronto-cingulo-parietal convergence, regions similarly identified when considering separate mathematical, verbal, and visuospatial problem solving domain-specific analyses. Conjunction analysis revealed a common network supporting problem solving across diverse contexts, and difference maps distinguished functionally-selective sub-networks specific to task type. Our results suggest cooperation between representationally specialized sub-network and whole-brain systems provide a neural basis for problem solving, with the core network contributing general purpose resources to perform cognitive operations and manage problem demand. Further

characterization of cross-network dynamics could inform neuroeducational studies on problem solving skill development.

2.2 Introduction

Problem solving has been investigated across human and animal models for decades; it is a process that is central to numerous everyday tasks involving the execution of a complex, multi-step sequence of goal-oriented objectives. In humans, problem solving has been used to quantify general intelligence (Jung and Haier, 2007; Savage, 1974), assess educational or learning outcomes (Hmelo-Silver, 2004; Jonassen, 1997; Pellegrino and Hilton, 2012; Yerushalmi et al., 2007), understand age-related cognitive declines (Mienaltowski, 2011; Paas et al., 2001), or characterize neurocognitive or developmental disorders (Kodituwakku, 2009; Ozonoff and Jensen, 1999; Sachdev et al., 2014), and has been investigated across multiple research domains including medicine (Elstein, 2002), economics (von Hippel, 1994), education (Jonassen, 2000; NCTM, 2010), physics (Hsu et al., 2004; Maloney, 2011), psychology (Davidson and Sternberg, 2003; Simon A. and Newell, 1971), and cognitive neuroscience (Fink et al., 2009; Unterrainer and Owen, 2006).

Given this universal and multidisciplinary interest in problem solving, numerous definitions of the construct have been articulated by experts from different domains with varying theoretical knowledge bases. In the present study, we adopt the definition of a *problem* as a "situation in which you are trying to reach some goal, and must find a means for getting there" (Chi & Glaser, 1985, pp. 229). The act of *problem solving* then involves identifying and/or performing critical thinking processes related to evaluating the problem, planning or sequencing actions to solve it, and executing operations that conform to some rule set (e.g., semantic, algebraic, logical, mechanical, or other delimiting frameworks) to arrive at a correct, or sometimes most appropriate, previously unknown solution. Within this operational definition, problem solving can be considered as a sequential and/or parallel orchestration of a series of integrative cognitive maneuvers wherein solutions are systematically, but not necessarily immediately, derived. Such framing acknowledges that problem solving encompasses iterative algorithmic steps, as well as exploratory and innovative processes wherein solution paths draw on creativity and insight. It is of note that an important component of solving a problem may be in the initial characterization of the problem itself, a step in which one must identify the rule set implied or relevant to the problem's context. In this way, the problem solving processes can be highly content-specific while simultaneously grounded in a common framework that is context-independent. Thus, problem solving-related processes are dynamic, frequently involve the confluence of learning, cognitive ability, and previously acquired knowledge, and span developmental stage and social context. Problem solving can range from formative human experiences such as a toddler interacting with environmental affordances as objects and tools are tested to replicate observed functions, to more technical or abstract undertakings such as scientists drawing on experiment, technique, and knowledge to address unresolved questions from their discipline.

In human functional neuroimaging research, numerous and diverse experimental tasks have been used to elicit cognitive processes viewed as central to problem solving. Various neuroimaging studies have considered problem solving from the perspectives of mathematical calculation (e.g., Dehaene et al., 1999), deductive or inductive reasoning (e.g., Goel, 2007), insight solution generation (e.g., Luo and Niki, 2003), verbal or picture-based analogical reasoning (e.g., Bunge et al., 2005), fluid intelligence (e.g., Prabhakaran et al., 1997), or puzzle solving and game-play (e.g., Atherton et al., 2003). However, little is known about the neurobiological processes underlying problem solving as a general endeavor, and a broad comparison of activation results across these multiple diverse problem solving tasks has not been conducted. Thus, it is not known if there exists a constellation of common brain regions supporting general problem solving, irrespective of topic, scope, or discipline, or if problem solving is a relatively specific mental activity that instead relies more strongly on particular neural correlates most relevant to the problem's specific context and features. By addressing this question, we may be better able to characterize the nature of problem solving across its many interdisciplinary conceptions in the service of facilitating improvements to strategies promoting problem solving skill development.

While problem solving remains a relatively equivocally defined construct, particularly within the neuroimaging literature, initial insight into the neural substrates of many of the constituent processes noted above may be gleaned from the *executive function domain*. For example, Minzenberg et al. (2009) and Niendam et al. (2012) characterized executive functions as those mental processes that direct, regulate, and integrate goal-oriented behavior. *Cognitive control* is a term often used synonymously with, or to emphasize the regulatory aspects of, executive function wherein many cognitive processes together dynamically manage information to guide actions and achieve a common purpose (Miller, 2000). This 'managerial system' responsible for directing necessarily coherent, purposeful, and stepwise actions is likely a central element across many, if not all, forms of problem solving. Yet, it remains unclear which of the neural correlates of cognitive control are also essential for problem solving, and whether a common network exists linked with problem solving across contexts.

Brain regions associated with executive function have been relatively well studied, are often collectively referred to as the Central Executive Network (CEN), and typically reveal functionally connected inter- and intra-hemispheric regions across association cortices. Early perspectives on executive function attempted to map specific and theoretically distinct cognitive processes onto individual brain regions (Luria, 1966; Shallice, 1988). However, as experimental techniques in fMRI deepened the scientific understanding of cognitive control, consensus shifted away from simple one-to-one function-structure mappings and towards a more system-based perspective wherein whole-brain distributed networks support multiple cognitive constructs (Carpenter, 2000; Menon and Uddin, 2010). Goal-oriented, complex cognition is maintained by such multiregional interactions (Cocchi et al., 2013), and intra-hemispheric frontoparietal connections may be one neurobiological aspect contributing to species-specific behavioral differences between human and non-human primates (Wey et al., 2013). The dorsolateral prefrontal cortex (dlPFC), medial prefrontal cortex (mPFC), and posterior parietal cortex (PPC) are together frequently implicated across executive function paradigms such as working memory *n-back* tasks (Owen et al., 2005; Curtis, 2003), attentional control tasks including *go/no-go* and *Stroop* paradigms (Cieslik, 2015), and others such as the *oddball* vigilance task, *tower maze* planning task, and *Wisconsin card sorting* flexibility task (Lie et al., 2006; Linden, 1999; Unterrainer and Owen, 2006).

In an extensive meta-analysis across executive function tasks, Niendam and colleagues (2012) considered 193 neuroimaging studies reporting outcomes from flexibility, inhibition, working memory, initiation, planning, and vigilance paradigms. Those authors identified a cross-domain cognitive control system including dlPFC, frontopolar cortex, orbitofrontal cortex, anterior cingulate cortex (ACC), superior and inferior parietal and occipito-temporal cortex, cerebellum, and limbic areas such as the caudate, putamen, and thalamus. This so-called *superordinate cognitive control system* constituted a shared network supporting various disparate paradigm activations, and thus suggested that multiple executive functions are supported across a common set of fronto-cingulo-limbic-parietal brain regions. Similar observations of common prefrontal, insular, and parietal brain regions responsible for a diversity of goal-oriented tasks have also been demonstrated across attentional processes (Duncan, 2006) and show enhanced involvement when task demands are increased, regardless the type of task performed (Duncan and Owen, 2000; Fedorenko et al., 2013). This system has been termed the *multiple demand* (MD) network because of its high flexibility across contexts and has been argued to be critically involved in task control, attentional focusing, managing cognitive load, and may play a central role in interfacing with different brain systems that accomplish sub-tasks or specific cognitive operations within structured mental operations (Duncan, 2013, 2010). Given the close ties between problem solving and this multitude of diverse cognitive functions, a reasonable working hypothesis is that a similar network is associated with problem solving across diverse representational domains.

While a collection of brain regions commonly activated across problem solving tasks may be indicative of a supervisory control network, there is also evidence for simultaneous domain-specific regional involvement during problem solving. Neural findings from individual problem solving studies support the notion of a supervisory control network that also subtends functionally specific regional interactions. For example, in an investigation of math and word problem solving, Newman and others (2011) identified a common set of CEN regions, including superior parietal lobule (SPL) and horizontal intraparietal sulcus (IPS), that supported both representational modalities of problem solving. In addition to this common problem solving network, they also observed distinct activations across Broca's and Wernicke's areas in word but not number problems, and identified enhanced activation in IPS specific to number but not word problems. These results highlight the importance of not only a common network for problem solving, but also the separate and distinctive interaction of regions specific to problem solving representation.

To date, results from the wide range of neuroimaging problem solving paradigms have not been collectively assessed to identify common and differential brain activation patterns across problem solving representational contexts and distinct domains. To this end, we first identified a set of published neuroimaging experiments that utilized high-level critical thinking and reasoning tasks. If the tasks were consistent with our operational definition of problem solving, we selected related experimental contrasts according to inclusion criteria. These tasks involved healthy adults answering novel questions by way of generating or verifying solutions. We then applied a quantitative, coordinate-based meta-analysis method to comprehensively synthesize this literature corpus with the purpose of identifying the neural networks associated with problem solving. Using this methodology, we sought to: (1) determine if convergent neurobiological substrates are present across the diversity of problem solving tasks; and conversely, (2) identify those brain regions exhibiting consistent functional specificity within distinct representation domains.

2.3 Methods

To identify consistent and dissociable brain activation patterns linked with problem solving, we conducted a series of Activation Likelihood Estimation (ALE) meta-analyses (Turkeltaub et al., 2002; Laird et al., 2005; Eickhoff et al., 2009; 2012; Turkeltaub et al., 2012) delineating convergent results reported within and across distinct representational categories.

2.3.1 Literature Search and Experiment Selection Criteria

We began by establishing our definition of problem solving, independent of any literature searches or reviews. Then, a search to compile a comprehensive set of peer-reviewed functional neuroimaging studies investigating problem solving published in English between January 1st 1997 and March 14, 2015 was performed across multiple literature indexing services, including PubMed (www.pubmed.com), Web of Science (www.webofknowledge.com), and Google Scholar (www.scholar.google.com). Searches were constructed to identify functional magnetic resonance imaging (fMRI) or positron emission tomography (PET) studies indexed by keywords such as problem solving, calculation, verbal reasoning, visuospatial reasoning, insight, deductive reasoning, inductive reasoning, or fluid reasoning. References within papers matching these search criteria were examined and appropriate studies not previously identified were added to the pool of potential papers for inclusion. To avoid bias introduced by the selection process, we gathered a large corpus of papers extending across a range of experiments, ensuring cluster convergence was not due to the particular studies selected but rather was representative of a general result across a spectrum of experiments. We determined if tasks in these studies were reasonably described by the two-part problem solving definition we had adopted (i.e., first having a goal, followed by a need to figure out a way to reach it). Once the set of problem solving tasks were identified, associated studies were filtered to identify problem solving experiments/contrasts that isolated one or more of the cognitive processes central to the problem solving task. Of those identified, we selected only those contrasts reporting either blood oxygen level dependent (BOLD) or regional cerebral blood flow (rCBF) signal increases; results associated with BOLD or rCBF decreases were excluded. Group-level effects in healthy adult individuals were targeted, while disease-, age-, and gender-related group comparisons were excluded. Experiments were further filtered to include only those that reported task-related increases as stereotactic coordinate results in either Talairach or Montreal Neurological Institute (MNI) standardized space. The final set of experiments was constrained to include only whole-brain analyses and exclude region of interest (ROI) results.

Three main paradigm groupings emerged as separate problem solving domains within the neuroimaging literature: tasks in which participants solved computational or *mathematical problems*, language-based or *verbal problems*, or picture-based or *visuospatial problems*. Representational domains were defined by the stimulus modality used: mathematical problems involved number manipulation, verbal problems presented questions with sentence, word, or letter stimuli, and visuospatial problems involved pictorial or spatial tasks. Within these representational sets, five distinct contrast types were included in the meta-analyses: contrasts in which (1) a baseline condition was subtracted from a problem solving task (i.e., problem solving > baseline), (2) problem solving questions were parametrically compared across varying difficulty, abstraction, or complexity (e.g., complex problem solving > simple problem solving), (3) untrained, previously unseen, and novel problems were solved and contrasted with previously memorized or solved problems of the same type (i.e., untrained problem solving > trained problem solving), (4) problem solving was compared across different rule sets or representational modalities (i.e., problem solving type 1 > problem solving type 2; e.g., multiplication problems > addition problems or word problems > number problems), or (5) distinct and sequential problem solving phases were contrasted with each other (e.g., problem solving late phase > problem solving early phase). Several studies used problem solving to investigate differences between healthy controls and either patient populations or populations with intellectually gifted individuals (e.g., mathematical prodigies or high-IQ individuals). Experiments were included from these studies if within-group results for healthy controls were separately reported, without any group interaction effects or comparison with an experimental group.

2.3.2 Activation Likelihood Estimation

Stereotactic coordinates were extracted from the identified set of problem solving contrasts. To reduce disparity between MNI and Talairach coordinates (Laird et al., 2010), foci originally reported in Talairach space were transformed into MNI space using the tal2icbm algorithm (Lancaster, 2007). A series of activation likelihood estimation meta-analyses was performed in the MATLAB environment to assess concordance across studies and within each problem solving representational domain using the revised non-additive ALE algorithm (Laird et al., 2005; Eickhoff et al., 2009; Turkeltaub et al., 2012). This random-effects approach models activation foci as three-dimensional Gaussian probability distributions whose widths reflect variances in experimental sample size and uncertainty inherent to spatial normalization. The ALE algorithm first computes a set of modeled activation (MA) maps by selecting the maximum probability associated with any one Gaussian within each experiment (Turkeltaub et al., 2012). This method was employed to alleviate artificial conflation of MA values due to within-experiment coordinate proximity and thus limits the maximum contribution any single experiment can have on the overall ALE results. After the within-experiment activations were modeled, voxel-wise focal overlap across experiments was determined by computing the union of all activation probabilities (known as the voxel's ALE score), a quantity representing convergence of results across studies. This union was anatomically constrained by a grey matter mask based on the ICBM tissue probability maps of Evans et al. (1994). Statistical significance within this so-called ALE map was determined by comparing the distribution of ALE scores to a null-distribution modeled by 10,000 permutations of random data, each containing identical characteristics to those of the actual experiments (e.g., simulated subject and foci numbers). Computationally, foci from the dataset were replaced with coordinates randomly selected from the gray matter template and the union of their values was computed to form the empirically derived null-distribution used to test the null hypothesis of randomly distributed activations. Then, above-chance clustering between experiments was assessed by computing P-values given by the proportion of ALE scores equal to or greater than those obtained under the null-distribution. A correction for multiple comparisons was implemented by using a voxel-level threshold of $P < 0.001$, and then ALE results were family-wise error (FWE) corrected at a cluster extent threshold of $P < 0.05$ (Eickhoff et al., 2017).

First, to identify *common activation patterns* across problem solving, coordinate results from all representational domains (i.e., mathematical, verbal, and visuospatial domains) were pooled and assessed for convergence. The resulting 'global network' was agnostic to variants in problem solving type and therefore useful in evaluating whether a content-general problem solving meta-analytic network could be identified. Here, and in following sections, we refer to the term 'meta-analytic network' (or simply 'network') as a collection of brain regions that together represent the common activation patterns resulting from meta-analytic results. Because clusters revealed by the global network need not be similarly observable across sub-domains, we performed follow-up characterizations of within-domain activation patterns to resolve context-relevant networks. To investigate which brain regions were consistently activated within content-specific tasks, we delineated experiments by representational domain and separately assessed coordinate convergence across mathematical, verbal, and visuospatial problem solving variants. We then inspected these within-domain ALE maps for three-way conjunctions to identify overlap indicative of common and convergent activation among all types of problem solving (i.e., a core network). Specifically, we conducted a conservative minimum statistic conjunction analysis (Nichols, 2005) to identify significant voxels commonly present across all domain-specific problem solving ALE maps.

Next, to decipher the functional role of this core network and identify specific cognitive processes contributing to problem solving in general, we performed functional decoding (which is a statistical approach used to determine psychologically-linked terms given observed brain activation patterns) on the resulting conjunction map (Poldrack, 2011). To do this, we fit a Generalized Correspondence Latent Dirichlet Allocation (GC-LDA; Rubin et al., 2016, 2017) model with 200 topics to the Neurosynth literature corpus (Yarkoni et al., 2011). The GC-LDA model associates each topic with a probability distribution across terms from article abstracts and with a spatial distribution (in this case as a bilateral pair of Gaussian distributions) across voxels in MNI space. These topics reflect words and foci which frequently co-occur across studies in the literature and facilitate distinguishing the conceptual structure associated with terms that can be imprecise or variously defined across studies. Next, we fed the conjunction map into the decoding algorithm, which used the $P(topic|voxel)$ distribution estimated by the topic model to estimate $P(topic|map)$. Finally, we expanded the topic weights to word weights by computing the dot product between the $P(topic|map)$ vector and the $P(word|topic)$ distribution estimated by the model.

Then, to statistically compare each problem solving domain and isolate *differential activations patterns* selective to each of the three problem solving types, we ran formal contrast ALE meta-analyses using methods described in detail in Laird et al. (2005) and Bzdok et al. (2015). These three-way ALE contrasts were determined by computing difference maps across pairs of domain-specific ALE images and then assessing the conjunction, using the minimum statistic approach, across the difference maps. For example, to isolate the brain activity specifically associated with mathematical problem solving, we first calculated the contrasts of *Mathematical – Verbal* problem solving and *Mathematical – Visuospatial* problem solving. We then computed the conjunction between these two differences (i.e., [*Mathematical – Verbal*] ∩ [*Mathematical – Visuospatial*]), which isolated brain regions uniquely contributing to mathematical problem solving separated from verbal and visuospatial modalities. Similar conjunction analyses were performed for verbal ([*Verbal – Mathematical*] ∩ [*Verbal – Visuospatial*]) and visuospatial specific contrasts ([*Visuospatial – Mathematical*] ∩ [*Visuospatial – Verbal*]). This method for computing the contrasts of multiple ALE images determines which clusters are statistically selective in one ALE map from those regions shared with all other ALE maps. Thus, we assessed domain specificity by examining if one task domain demonstrated greater convergence compared to both of the other task domains. All contrast analyses were generated with voxel-wise thresholding at $P < 0.01$ (false-discovery rate corrected) using 250 mm^3 minimum cluster volumes and 10,000 permutations. The anatomical locations of the observed clusters are labeled and reported in MNI space.

Lastly, we conducted a meta-analysis in which we considered the role of *cognitive demand* within problem solving. Our approach in this analysis was similar to that previously adopted by Duncan and Owen (2000) in their observation of the multiple demand network. We selected contrasts for this final meta-analysis that compared high to low demands across problem tasks (i.e. Complex > Simple Problem Solving) that were otherwise identical. In this way, we assessed convergence across a range of different problem solving experiments, each of which isolated the specific neural underpinning associated with problem difficulty while still controlling for additional factors potentially impacting demand (e.g. task type).

2.4 Results

2.4.1 Literature Search Results

The results of the problem solving literature search across mathematical, verbal, and visuospatial domains are described in detail below; the specific contrasts are detailed in **Table A.1**, along with the numbers of foci and subjects, task, stimulus, contrast classification, and neuroimaging modality.

2.4.1.1 Mathematical Problem Solving Paradigms

Numerical calculation was the most widely studied representational domain within the neuroimaging problem solving literature. Overall, the literature search identified 99 mathematical problem solving contrasts, yielding 1,044 activation foci from 41 published papers. A total of 65 of these contrasts compared problem solving with a rest or low-level baseline condition, 21 contrasted two different forms of mathematical problem solving, and 13 compared complex versus simple conditions. Although operand tasks took varying forms, basic paradigm structure involved mental binary operations (i.e., addition, subtraction, multiplication, division) being performed on integer Arabic numerals to arrive at single valued answers. A 2011 meta-analysis on number sense and calculation (Arsalidou and Taylor, 2011) previously identified several mathematical problem solving studies relevant to the investigation at hand. Thus, these experiments were included in this meta-analysis, along with additional neuroimaging studies matching our inclusion criteria. Included paradigms are further described below and in **Table A.1a**.

Number Operation Tasks

The majority of included calculation paradigms involved mental quantity manipulations of either one- or two-digit Arabic numerals so as to generate, select, or verify solutions to mathematical expressions (e.g., “6 + 8” or “12 x 55”). Most number operation tasks presented two numeric values on which a single binary operation was performed. However, tasks of this class also included operand manipulations on multi-number lists. Participants responded to numerical and symbolic stimuli by either overtly speaking solutions, internally identifying them, or using a button press to select the correct value from a list of answer choices. Calculation verification paradigms presented participants with numerical equations such as “5 – 13 = -8” and participants decided if the statements were true or false. Most numerical operand paradigms utilized visual stimuli of Arabic digits and/or binary mathematical operands, however some tasks also presented subjects with Roman numerals, auditory Arabic numerals, or English words of Arabic numerals.

Baseline or control conditions for operand tasks took one of several forms including identifying, matching, or comparing target number values. In identification conditions, participants overtly recited values or pressed a button when a target number, letter, word, or symbol appeared on a screen. Baseline matching conditions instructed participants to select an identical number to a previously presented stimulus. In comparison tasks, participants viewed number pairs and identified the digit of larger value. Number comparison, which is sometimes used to measure numeric distance or number sense, did not fit our cognitively demanding definition for problem solving; thus, we considered these tasks as appropriate high-level control conditions for calculation tasks (i.e., Calculation > Comparison).

The present meta-analysis additionally included high-level contrasts such as Multiplication > Addition, Complex > Simple, Number Problems > Word Problems, or Exact Calculation > Approximation. While these control conditions were themselves instances of problem solving, their cognitive subtractions yielded coordinate results specific to characteristics central in mathematical problem solving (i.e., in the respective above examples these were operand type, difficulty level, representation modality, solution method). Because we sought to include results from multiple varieties of questions and across characteristics, we likewise included reverse contrasts such as Addition > Multiplication and so on. Although these reverse contrasts yielded disjoint sets of activation patterns, we considered each contrast as an independent experiment targeting specific qualities inherent to mathematical problem solving. Because both sets of coordinate results highlighted specific characteristics within the general umbrella of mathematical problem solving, they were included. The literature search produced 80 (out of 99 total mathematical problem solving) number operations contrasts associated with 776 activation foci from 30 papers for inclusion in the meta-analysis.

Paced Auditory/Visual Serial Addition Test

The paced addition serial attention test (PASAT), modified PASAT (mPASAT), or paced visual serial attention test (PVSAT) are neuropsychological tests widely used to study cognitive impairments, attention, information processing speed, and working memory

(Tombaugh, 2006). The primary procedure in this paradigm involves mentally and serially adding digits together. Participants are presented with either an auditory (PASAT or mPASAT) or a visual (PVSAT) sequence of numbers, with individual digits ranging between 0 and 9, and are instructed to mentally add the first and second numbers. This sum is then mentally added to the third value, and so on, until the sum of digits equals 10. The participant indicates the sum equals 10 with a button press or hand gesture and begins the serial summation again. While the paradigm has been used to investigate working memory (Lazeron et al., 2003; Mainero et al., 2004) this calculation task employs sequential addition of an unknown number of random digits until a final value is determined. Thus, the paradigm implicates multi-stepped analytical thinking within the rule set of addition until completion, with the goal of correctly identifying the closing number in the additive sequence. Accordingly, we characterized the PA/VSAT task as a mathematically-based problem solving paradigm and included these tasks in the mathematical meta-analysis. The literature search yielded 7 (out of 99 total mathematical problem solving) PA/VSAT contrasts, which included 138 activation foci from 6 papers.

Additional Mathematical Tasks

Several neuroimaging paradigms targeted mathematical problem solving processes employing less common number or math-based stimuli. Such tasks included percent estimation problems ("what is 44 percent of 70?"; Venkatraman et al., 2006), equation-based algebraic or calculus problem manipulations (Krueger et al., 2008; Newman et al., 2011), or other algorithm-based problems such as pyramid problems (Delazer et al., 2005) or number bisection problems (Wood et al., 2008). In pyramid problems participants viewed non-standard operation expressions such as 54$3 and were trained to perform the corresponding "$" algorithm (in this example, 54+53+52 where 54 is the 'base number' and 3 is the 'addition span number'). Number bisection problems cued participants with ordered number triplets such as (44,62,87) and participants determined if the middle value was also the mean of the flanking numbers. The literature search yielded 12 additional (out of 99 total) mathematical contrasts reporting 130 activation foci from 5 papers for inclusion in the meta-analysis.

2.4.1.2 Verbal Problem Solving Paradigms

Neuroimaging problem solving paradigms in the verbal domain asked questions via letter, word, or sentence stimuli, and participants used logic or content knowledge to comprehend, generate, or identify solutions. Overall, the literature search identified 93 verbal problem solving contrasts, which reported 1,028 activation foci from 43 published papers. Of the 93 verbal contrasts identified, 49 compared problem solving with a baseline condition, 13 contrasted complex to simple problem solving in the verbal domain, 22 contrasted differing types of verbal problem solving, 7 identified activation at distinct problem solving phases by contrasting distinct stages in the problem solving process, and two compared untrained to trained verbal problem solving. Paradigms in this category included deductive and inductive reasoning sentences, riddles and insight questions, paragraph-based word problems, and word or letter string analogy sets. These paradigms displayed diversity in stimuli and reasoning methods used, and participants responded via button press to either select from a set of solution options, indicate if a given problem was logical or illogical, or if they had been successfully able to arrive at a solution to the verbal problem before the time expired and an answer was revealed. Included paradigms are described below and in **Table A.1b**.

Deductive Reasoning Paradigms

Deduction is a logical process in which specific conclusions are inferred from general rules. Neuroimaging paradigms typically explore mechanisms supporting deductive reasoning across categorical (e.g., All A's are B's, All B's are C's, therefore all A's are C's), relational (e.g., A is to the right of B, B is to the right of C, A is to the right of C), or propositional (e.g., If A then B; A; Therefore B) argument types. In these paradigms, subjects considered sentence- or letter-based arguments and determined if a given conclusion logically followed from the premises. Participants were instructed to respond to questions by pressing a button to indicate if the argument was valid or invalid. Deductive reasoning control conditions typically asked logic questions whose answers were trivially false (e.g., "if A is to the right of B and B is the right of C, is D is to the right of F?") A 2011 neuroimaging meta-analysis (Prado et al., 2011) of deductive reasoning tasks served as an initial model for studies included in our language-based problem solving analysis. We included appropriate studies from this deduction meta-analysis and updated and extended the corpus of deductive linguistic papers for the present study.

While the majority of included verbal deductive reasoning paradigms took one of the conditional forms described above, several paradigms also included in this category presented linguistically challenging word problems that required logical deduction. For example, in Newman et al. (2011) participants viewed statements such as, "The day before my favorite day is two days after Thursday", and then determined which day was the favorite. Another study (Kroger et al., 2008) presented word problems such as, "There are five students in a room. Three or more of these students are joggers. Three or more of these students are writers. Three or more of these students are dancers. Does it follow that at least one of the students in the room is all three: a jogger, a writer, and a dancer?". Some of these studies, as in Zarnhofer et al. (2013), asked participants to solve arithmetic word problems (e.g., "Anna goes for a walk. She walks 4 km/h. What distance does she cover in 3 hours?"). These problems, although mathematical in nature, were included in the verbal meta-analysis because their stimuli were sentence-based. The literature search produced 60 (out of 93 total verbal problem solving) deductive reasoning contrasts associated with 688 activation foci published in 25 papers for inclusion in the meta-analysis.

Verbal Inductive/Probabilistic Reasoning Paradigms

While deductive reasoning is used to make claims on specific information by applying general rules, inductive reasoning is a procedure by which broad rules are inferred from particular instances (e.g., "Mike is a basketball player, Mike is tall. All basketball players are tall."). While counterexamples can disprove inductive reasoning statements, they can never be fully logically proved. Thus, in inductive neuroimaging paradigms, participants determine if the concluding statements are plausible or not plausible. These inductive tasks are sometimes also referred to as probabilistic reasoning tasks.

Paradigms in this category frequently took a categorical form and the task was to determine of the statement had a greater chance of being true or false (e.g., "House cats have 32 teeth; Lions have 32 teeth; All felines have 32 teeth?"; Goel and Dolan, 2004). Other probabilistic paradigms included in this analysis presented participants with event frequencies from hypothetical experiments with known outcomes and participants probabilistically determined which experiment the results came from. For example, in Blackwood et al. (2004), participants viewed a serial presentation of positive and negative words. They were told these words had been drawn from a survey that received a positive to negative response ratio of either 60:40 or 40:60. Participants were asked to choose which survey the viewed words had likely been drawn from. The literature search yielded 5 (out of 93 total verbal problem solving) inductive reasoning contrasts that included 34 activation foci from 4 papers for inclusion in the meta-analysis.

Verbal Analogy Problems

Analogical reasoning relies on the ability to draw conclusions about relationships from given information and/or by using background knowledge. Typical analogy problems across the neuroimaging literature, such as those in Luo et al. (2003), present participants with dual word pairs and subjects determine if these formed analogous or general semantically related sets (e.g., analogy: "drummer, band" = "soldier, army"; semantic: "refrigerator, kitchen" = "lounge, room"). Other linguistic analogy tasks were sentence-based and asked participants to complete phrases such as, "black is to white and high is to ….?" (Wendelken et al., 2008). We also included analogy tasks in this meta-analysis that involved semantic word retrieval (Wagner et al., 2001) in which participants viewed a cue word and then target words that were either unrelated, weakly related, or strongly related to the cue (e.g., strongly related: "cue = rain; targets = pillow, puddle, book, sneaker"; weakly related: "cue = candle; targets = design, halo, exists, bald"); subjects selected the target word most related to the cue.

Analogy tasks sometimes used purely letter-based representations; for example, in Geake and Hansen (2005) participants viewed two successive non-word letters strings that revealed an order- or alphabetic-based transformation rule (e.g., ird implies dri). Subjects were then shown a third letter string and choose or generated the letter string that best followed the transformation rule (e.g., ykw implies ?). Many so-called "fluid analogy" problems, such as in this example, required both semantic and content knowledge to choose the most plausible answer. A similar paradigm, drawn from the Educational Testing Service Kit of Factor Referenced Cognitive Sets (Ekstrom et al., 1976), presented participants with non-word letter strings with some common alphabetic or translational rule, and participants were asked to identify the "odd one out" from a set of choices (Duncan et al., 2000). The literature search produced 9 (out of 93 total verbal problem solving) analogy contrasts that reported a total of 78 activation foci from 5 papers.

<u>Insight Problem Solving</u>

Insight question paradigms are language-based paradigms that targeted the "aha" moment within problem solving and frequently take the form of sentence- or character-based riddle problems. Riddle solving involves careful consideration of phrasings and/or semantic indicators such as syntactic or logographic structure. Neuroimaging riddle paradigms, such as in (Luo and Niki, 2003), used problems like "What can move heavy logs, but cannot move a small nail?" (solution: "a river"). Other riddle-like paradigms relied on word play within Chinese character idioms (or "Chengyu") whose figurative meanings are often distinct from their literal ones (e.g., an English-language idiom of similar kind is "kick the bucket", which has the figurative meaning "to die"; Zhang, 2012). The goal of these paradigms is to identify the expression's metaphoric meaning by decomposing constituent characters into meaningful semantic chunks. For example, in Qiu et al. (2010), participants were given phrases such as 右眼难见, which translates to "having eyes but being unable to see", and were asked to derive the idiom's underlying meaning. In this case, the answer is 盲 (which means "blind"), and is derived by combining the phonetic symbol 亡 with the semantic radical 目 that appears as a constituent chunk in the Chengyu component 眼. Insight paradigms based on chunk decomposition of logograms took multiple but similar forms in the neuroimaging literature and appropriate studies were included in this meta-analysis.

Other neuroimaging paradigms that study insight are anagrams puzzles in which letters from words have been scrambled beyond the point of recognition. Participants, such as those in Aziz-Zadeh et al. (2009), were presented with these scrambled words and are asked to determine the original word. Several additional non-standard insight problem solving paradigms were identified as appropriate for this meta-analysis; one such study (Luo et al., 2013) considered insight in scientific problem solving specifically. In that study, subjects were presented with paragraph-based real world scientific and engineering questions, some of which contained explicit hints towards a solution path. Participants were asked to determine solutions to these scientific/engineering questions and insight moments were facilitated by heuristic use. The literature search yielded 19 (out of 93 total verbal problem solving) insight contrasts reporting 215 activation foci from 12 papers.

2.4.1.3 Visuospatial Problem Solving Paradigms

In our third and final representational domain, we identified neuroimaging experiments using visuospatial problem solving to study analogic or relational reasoning by pattern identification, visualization, induction, and visual processing. Overall, the literature search identified 88 visuospatial problem solving contrasts which reported 1094 activation foci published in 50 papers. A total of 47 of these contrasts took the general form of visuospatial problem solving versus a baseline condition, 14 considered complex versus simple visuospatial problem solving, 16 contrasted two types of visuospatial problem solving, 10 contrasted untrained to trained visuospatial problem solving, and one contrasted problem solving across different phases. The visual problems sets identified as part of this literature search varied significantly across studies and many experiments in this representational domain utilized novel task paradigms. In all included visuospatial problem solving paradigms, participants used reasoning to respond to picture stimuli. Included paradigms are described below and in **Table A.1c**.

Visuospatial Fluid Reasoning Tasks

Fluid reasoning (sometimes called fluid intelligence, “Spearman's g”, or simply “Gf” or “g”; Spearman, 1928) is the ability to reason in novel situations, independent of prior knowledge or culturally embedded context (Ferrer et al., 2009). Two canonical neuropsychological paradigms frequently used to investigate the visuospatial component of fluid reasoning are the Raven’s Progressive Matrices (RPM; Raven, 2000) and the

Cattell's Culture Fair Test (Cattell, 1973). In the former, participants view 3 x 3 picture grids whose images progress horizontally and/or vertically by an analogical rule. Participants must determine the rule(s) of progression and, from a set of options, choose the image that completes the final grid entry. Similarly, the Culture Fair Test presents a set of drawings sharing a relational rule. Participants identify this rule and select either the "odd one out" from the image set, or choose an additional image that follows similarly. Each paradigm contains problems that parametrically increase in complexity level ("low" to "high" g) and simple problems are often used as control conditions to more complex fluid reasoning questions.

Variations of these two visuospatial reasoning tasks have been used across the literature and were also included in this meta-analysis. The Nagliri Nonverbal Intelligence Test (Kalbfleisch et al., 2007), the Fluid Intelligence Test (Ebisch et al., 2012), the Geometric Analogical Reasoning Task (Preusse et al., 2011), and the Nonverbal Reasoning Task (Hampshire et al. 2011) all require subject's use of relational integration abilities to identify visual pattern-based rules and make rule-based judgments on images. The literature search produced 19 (out of 88 total visuospatial problem solving) fluid reasoning contrasts associated with 200 activation foci from 11 papers that were included in the meta-analysis.

Visual Analogy Problems

Similar to fluid reasoning paradigms, visual analogy problems use picture-based stimuli to depict a deducible visuospatial rule set. In these types of tasks, participants viewed dual shape or image pairs (with A:B and C:D structure) that were related via pattern, color, geometric form, or physical appearance. Participants selected the answer that followed the visual analogical rule or indicated if an item did or did not follow that rule. For example, in Watson and Chatterjee (2012), problems presented colored shape strings illustrating a progression rule and participants choose from answer options putatively illustrating the same rule (e.g., target: red triangle, blue triangle, red circle; answer options: red diamond, blue diamond, red diamond or red diamond, blue diamond, red square). Similarly, Preusse et al. (2010) used a task where the rule set was given by mirror symmetry of geometric ensembles. Participants in this study viewed dual square grids in which blocked shapes depicted transformations about vertical, horizontal, and/or diagonal axes. The task was to indicate if a second grid pair followed the same reflection rule as the first.

Not all analogical problems of this category portrayed visual rules via abstract shapes. For example, Cho et al. (2010) used the People Pieces Analogy Task (Sternberg, 1977) to elicit analogical reasoning by presenting subjects with two analogical pairs of drawings of human forms. Each pair shared some common quality (e.g., width, height, gender…) and participants were given a list of these dimensions. They were asked if dual sets of people pairs correspond across a given dimension. This task involved problem solving across scales of both relational complexity and levels of attention interference. The literature search across visual analogy problems yielded 5 (out of 88 total visuospatial problem solving) analogical reasoning contrasts reporting 28 activation foci from 4 papers.

Tower of London Task

In the Tower of London (TOL) (Shallice, 1982) or Tower of Hanoi task (Zhang and Norman, 1994), participants are presented with an initial and target configuration of stacked colored balls or disks (e.g., red, green, blue) that lie along three columns. These colored objects can be moved one at a time and from the top of each stack, and placed on the top of any of the three columns. Participants are tasked with identifying the minimum number of moves needed to transform an initial arrangement into a final configuration. This paradigm is frequently used as an assessment of planning within problem solving. Control tasks for TOL sometimes involved simply counting the number of balls present in a configuration or watching balls change positions and counting the number of moves (Wagner et al., 2006). The literature search yielded 12 (out of 88 total visuospatial problem solving) Tower of London and Tower of Hanoi contrasts containing 161 activation foci, as reported in 9 papers included in the meta-analysis.

Spatial Navigation Problem Solving Tasks

Navigation neuroimaging paradigms generally focus on probing the neural mechanisms of spatial memory (e.g., task objective: "remember the location of objects/places encountered in a virtual environment and recall the placements later) or spatial planning and learning (e.g., task objective: "find your way from a starting point to a target location within a map/virtual environment.") Tasks of the latter variety aligned with our operational definition of problem solving and appropriate experiments of this kind were included in the present meta-analysis. Experiments displayed pictures of mazes or maps from allocentric or egocentric reference frames, and baseline conditions often took the form of route following along visually guided paths. We included relevant experiments identified in a 2014 neuroimaging meta-analysis of spatial navigation (Boccia et al., 2014) and updated and extended the corpus of navigation problem solving papers for the present study.

The majority of included tasks asked participants to make one or several critical decisions at intersection points during navigation, and subjects learned through trial and error which sequence of decisions led to the desired end location. Other contrasts involved navigating mazes that had been learned during a training session but that appeared within scanning as shuffled or with significantly altered visual features, making navigation difficult or in some cases impossible. Tasks of this type sometimes involved navigation along learned routes containing unexpected features inhibiting passage (e.g., a “roadblock” requiring detour planning as in Campbell et al., 2009 or Iaria et al., 2008). Spatial navigation tasks not included in this study were those that lacked the crucial problem solving component of figuring out a means in order to reaching the task goal, for example tasks wherein participants memorized a spatial layout during training and traversed the same environment during scanning, paradigms involving navigation from one familiar landmark to another within a participant's home city, or tasks in which the target location was clearly visible from the starting location. The literature search yielded 39 (out of 88 total visuospatial problem solving) visuospatial navigation problem solving contrasts associated with 531 activation foci from 18 published papers for inclusion in the meta-analysis.

Visuospatial Relational Reasoning

As in verbal deduction paradigms, relational reasoning problems in the visuospatial domain explore transitive inference across relational argument types (e.g., A is to the left of B, B is to the left of C, A is to the left of C). Typically, participants completing these tasks undergo initial out-of-scanner training where they encode multiple ordered shape pairs (e.g., A<B, B<C, C<D, and so on). Taken together these pairs implicitly represented elements drawn from an ordered shape string (e.g., A<B<C<D<…<N). Then, during MRI scanning, participants viewed non-sequential pairs of encoded relational shapes and selected the right-most shape (e.g., C in A<C or D in B<D; Acuna, 2002; Heckers et al., 2004).

Variations on these relational paradigms involved conditional rule completion or falsifications tasks wherein participants viewed colored shape configurations and were asked if they could complete or falsify a relational rule (e.g., "if there is not a red square on the left, then there is a yellow circle on the right"; Eslinger et al., 2009; Houdé et al., 2000). One such falsification task depicted five colored balls of equal or unequal weights appearing across four balance scales (Wendelken and Bunge, 2010). The scales were drawn balanced or tipped to indicate the relative ball weights. The task was to determine if a fifth scale drawing violated or verified the inferred weight rule. The literature search produced 6 (out of 88 total visuospatial problem solving) relational reasoning contrasts associated with 75 activation foci from 5 papers.

Visual Inductive/Probabilistic Reasoning Paradigms

Inductive reasoning paradigms wherein general rules are inferred from specific instances were less ubiquitously used in the visuospatial domain. However, appropriate paradigms that presented visual information and asked participants to decide on generalizable rules or plausible answer choices were included in this analysis. In one such task (Goel and Dolan, 2000) participants considered sets of animal drawings where the animal's physical characteristics (e.g., tail length, abdomen shape) varied along several degrees of similarity. The task was to generate a rule to determine if all animals in a set were likely of the same species. Another task (Blackwood et al., 2004) showed serial images of blue and red balls and participants determined if the balls had been drawn from a bottle containing either a 40:60 or a 60:40 ratio of blue to red balls. In another task (Lu et al., 2010) participants viewed inverted triangles displaying numeric values at each vertex. Each triangle followed a known (e.g., left – right) or unknown (e.g., bottom + right = left, right + left = bottom) calculation rule. Participants performed simple calculation (control condition) or inferred the triangle's rule from a target triangle and then applied that rule to a new triangle (activation condition). We included this paradigm in the visuospatial problem solving meta-analysis, even though numerical calculation was involved, because the target problems used visuospatial stimuli to illustrate spatially encoded induction rules. The literature search yielded 4 (out of 88 total visuospatial problem solving) inductive reasoning contrasts associated with 46 activation foci from 3 published papers for inclusion in the meta-analysis.

Additional Visuospatial Tasks

We also included visual problem solving within game-play contexts. Strategy-based board games such as Chess or Go involve abstract reasoning, planning, and visuospatial processing. Although not prevalent in the literature, some studies (Atherton et al., 2003; Chen et al., 2003) have investigated the neural correlates involved in this level of strategic game-play. Participants in these experiments viewed in-progress game boards and either identified the position of target pieces (control condition) or determined the best next move within a mid-game board configuration (activation condition). The literature search yielded 3 (out of 88 total visuospatial problem solving) additional visuospatial contrasts containing 53 activation foci from 2 papers.

2.4.2 Global Meta-Analysis

After completing the literature search, an ALE meta-analysis was performed across the total set of 131 papers that examined problem solving within all modalities and paradigms to identify convergent brain regions associated across all problem solving task described above. When multiple contrasts were reported within a single paper they were modeled as separate experiments provided they met our inclusions criteria (with 2.10 contrast included on average per paper, and no single paper contributing more than seven separate contrasts.) **This global problem solving meta-analysis included 280 contrasts, which reported a total of 3,166 foci from 1,919 individuals.** Convergence across experiments was observed in the frontal and parietal cortices, bilaterally including the superior, middle, and inferior frontal gyri (SFG, MFG, and IFG), as well as the dlPFC, dorsomedial prefrontal cortex (dmPFC), and ACC (**Figure 2.1**; coordinates listed in

Table 2.1). Bilateral parietal regions were observed across the medial posterior parietal cortex including the SPL, inferior parietal lobule (IPL), and precuneus. In addition to these frontoparietal clusters, consistent activation was observed in the bilateral anterior insular cortex (aIC), extending into the claustrum, lentiform nucleus, caudate, and anterior thalamus. Primary visual regions were also implicated in problem solving with bilateral convergence occurring in the inferior and lateral occipital gyri (IOG and LOG), including the lingual gyrus (LG) and fusiform gyrus (FG).

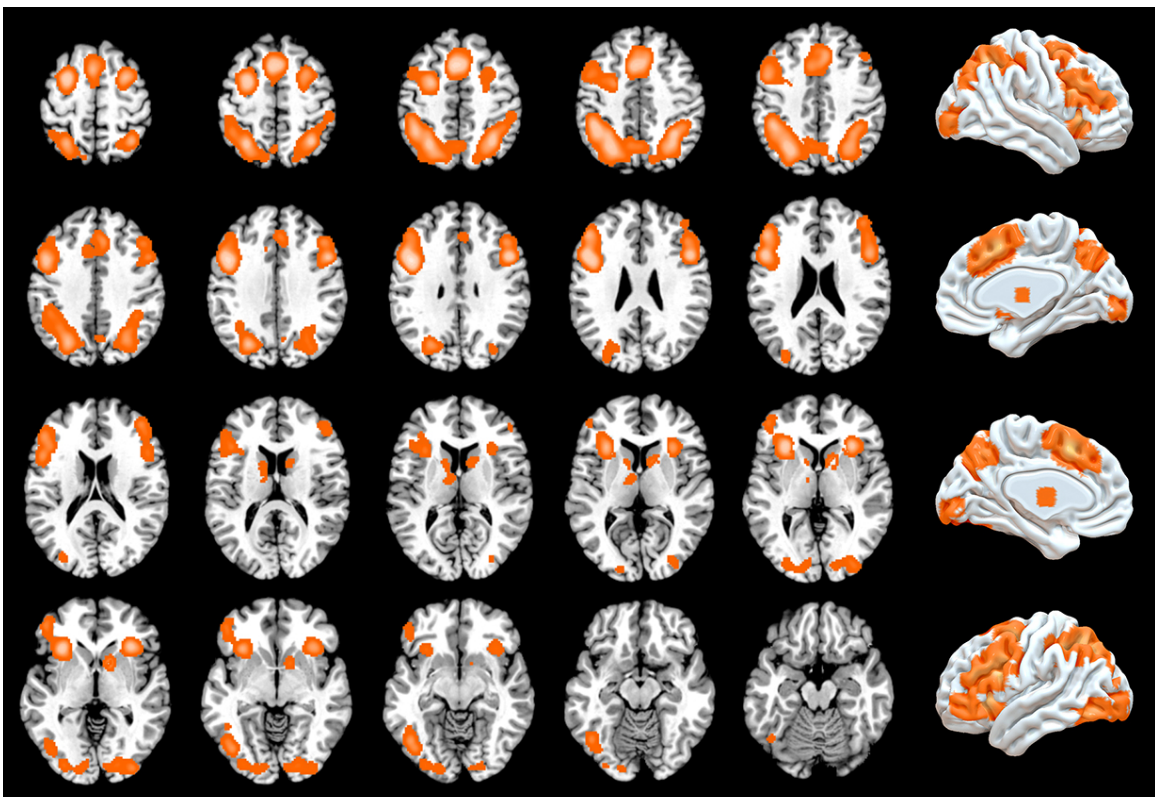


Figure 2.1. Global Problem Solving Meta-Analysis. The global problem solving meta-analysis identified convergence across 131 papers reporting coordinate results from a diverse range of problem solving experiments. Multiple problem solving modalities were represented in this set, with 280 experimental contrasts across 1,919 subjects. The broad engagement across whole-brain systems depicted by this map represents the overall neural underpinnings of problem solving.

Table 2.1. Coordinates of convergent activation from the global problem solving meta-analysis.

Global Problem Solving Meta-Analysis: Cluster Results

Cluster	Center of Mass (MNI space)			Cluster Extent (mm^3)	Mean ALE Score
	X	Y	Z		
1	-8	-60	44	43272	4.964
2	-40	14	28	34880	5.142
3	0	16	48	14136	5.195
4	48	22	26	10424	4.716
5	34	24	-2	4376	4.997
6	28	4	56	4152	4.715
7	26	-90	-2	3944	3.877
8	-44	-68	-10	3392	4.342
9	-22	-90	-6	3256	3.653
10	12	8	0	1824	4.033
11	-10	-2	8	1184	3.546

2.4.3 Mathematical Problem Solving Meta-Analysis

We next investigated 99 experiments reporting a total of 1,044 foci across 41 papers wherein 560 participants completed mental mathematical problem solving tasks using number, mathematical symbols, and/or letter- or symbol-based stimuli. Significant ALE-based convergence across these studies was observed in the frontoparietal cortices, including the dlPFC, dmPFC, ACC, SPL, IPL, and precuneus (**Figure 2.2A**, **Table 2.2a**). Similar to the global analysis, multiple bilateral MFG clusters were observed alongside convergence in SFG extending into the ACC. Peak ALE scores were observed in large bilateral clusters centered about the IFG, aIC, and in portions of anterior prefrontal cortex (PFC). These frontal regions included somewhat larger left-lateralized ALE clusters. In addition to frontal regions, sizeable posterior parietal clusters were observed in the supramarginal gyrus as well as bilateral IPL and SPL. Unlike other representation-specific analyses, the mathematical problem solving analysis displayed bilateral occipital convergence in the IOG, LOG, FG, and LG.

2.4.4 Verbal Problem Solving Meta-Analysis

Convergence across 93 verbal-based problem solving experiments reporting 1,028 foci in 43 papers and including 650 participants was next tested. Similar patterns of convergence occurred across the bilateral dlPFC, dmPFC, and posterior parietal regions, although somewhat smaller clusters were observed compared to the calculation analysis (**Figure 2.2B**, **Table 2.2b**). Verbal problem solving revealed left-emphasized MFG convergence extending from precentral gyrus / presupplementary motor area (Pre-SMA), across dlPFC, left MFG, and left orbitofrontal cortex. Specific to this domain were clusters in the left-lateralized middle temporal gyrus as well as bilateral thalamus. Convergence was also observed in the LG, and clusters were observed in the cerebellar uvula and pryamis/tuber.

2.4.5 Visuospatial Problem Solving Meta-Analysis

The third and final domain-based ALE meta-analysis included 88 experiments revealing 1094 activation foci appearing in 50 papers in which 745 participants engaged in picture-based problem solving tasks. Within the visuospatial domain, problem solving meta-analysis revealed similar regions of convergence as in the global as well as language- and mathematical-based problem solving analyses, including medial posterior parietal cortex, bilateral horizontal IPS, right SPL, precuneus, bilateral aIC, and bilateral mid and superior frontal gyri (**Figure 2.2C**, **Table 2.2c**). Multiple precuneus, posterior cingulate, parahippocampus, and retrosplenial cortex clusters were observed for this visuospatial analysis that were not revealed by the other representational domains. Additionally, the cortical clusters were overall more strongly lateralized compared to the mathematical and verbal meta-analyses, and larger regions of dlPFC convergence were observed in the right compared to left hemisphere.

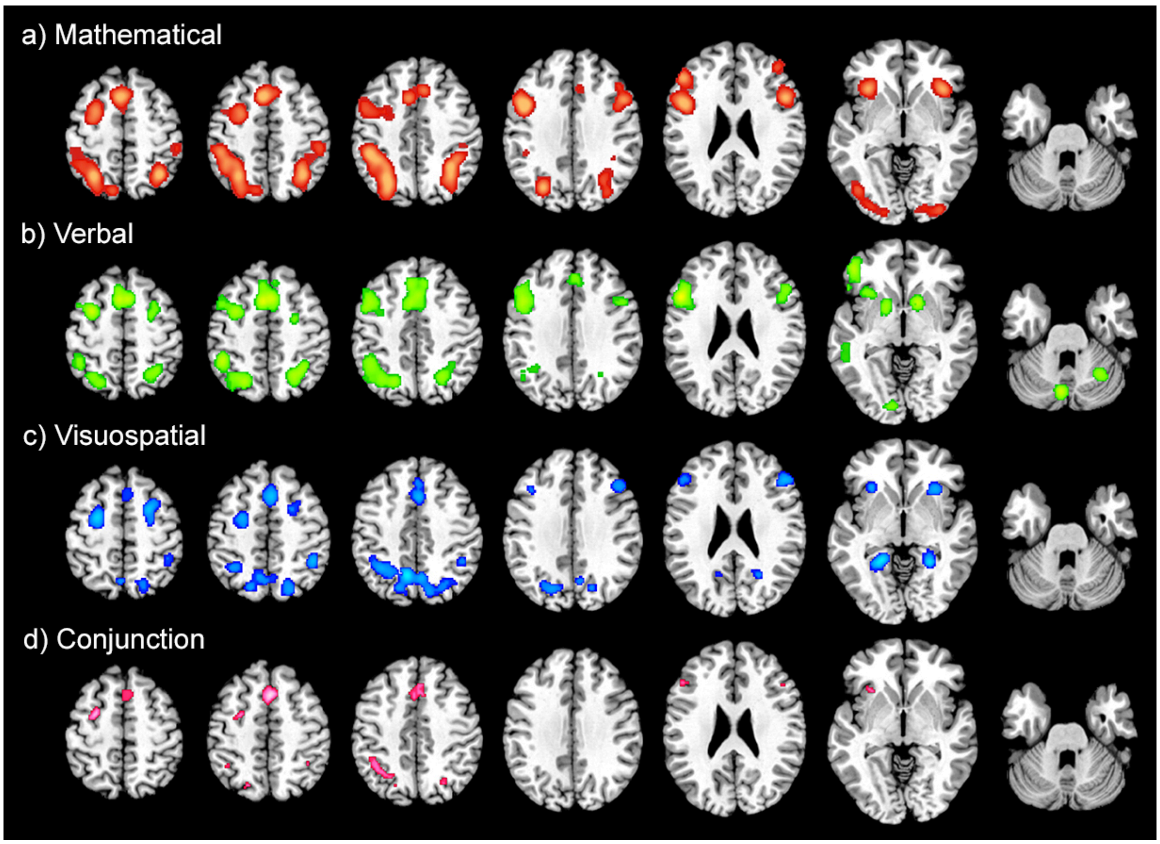


Figure 2.2. Representational Domain-specific and Conjunction Problem Solving Meta-Analyses. Problem solving experiments were categorized into three representational variants. Within-domain meta-analytic maps are shown for (a) mathematical problem solving (red) = 99 experiments, (b) verbal problem solving (green) = 93 experiments, and (c) visuospatial problem solving (blue) = 88 experiments. A common set of brain regions, present across this heterogeneous set of 280 problem solving contrasts, is depicted in (d), which shows the minimum statistic conjunction between all three within-domain maps (pink).

Table 2.2. Coordinates of convergent activation from the (a) mathematical, (b) verbal, and (c) visuospatial problem solving meta-analyses.

a) Mathematical Problem Solving Meta-Analysis: Cluster Results

Cluster	Center of Mass (MNI space)			Cluster Extent (mm^3)	Mean ALE Score
	X	Y	Z		
1	-40	12	28	23472	4.757
2	-32	-58	46	20760	4.952
3	34	-56	46	12232	4.667
4	-2	14	50	8520	4.587
5	-38	-78	-8	6000	4.090
6	48	14	26	5776	4.554
7	36	22	-2	4048	4.602
8	30	-92	-2	2136	3.881
9	44	44	18	1744	4.158

b) Verbal Problem Solving Meta-Analysis: Cluster Results

Cluster	Center of Mass (MNI space)			Cluster Extent (mm^3)	Mean ALE Score
	X	Y	Z		
1	-44	12	32	15312	4.338
2	0	18	46	9480	4.319
3	-36	-58	46	9040	3.971
4	28	-58	48	3912	4.052
5	-46	42	-4	3096	4.058
6	-56	-38	2	2296	3.895
7	46	16	26	2056	3.709
8	14	10	-6	1536	4.127
9	28	0	56	1528	3.713
10	-32	18	-2	1472	3.861
11	-6	-76	-32	1296	4.356
12	-16	6	-2	1248	4.057
13	32	-60	-32	1088	3.837
14	-14	-90	-6	1072	3.594

c) Visuospatial Problem Solving Meta-Analysis: Cluster Results

Cluster	Center of Mass (MNI space)			Cluster Extent (mm^3)	Mean ALE Score
	X	Y	Z		
1	-6	-64	44	12112	3.717
2	-26	-2	56	3848	4.211

3	26	2	56	3104	3.990
4	46	28	28	2912	3.761
5	-22	-48	-8	2832	4.169
6	2	18	46	2424	3.895
7	26	-44	-8	2136	4.228
8	16	-50	10	1920	3.638
9	-30	22	2	1672	3.902
10	-14	-56	10	1504	3.597
11	30	22	-4	1416	3.787
12	-46	30	26	1000	3.551
13	42	-46	48	984	3.820

2.4.6 Conjunction Across Domains

Next, we sought to identify a core set of brain regions commonly linked with problem solving across all representational domains by performing a conjunction analysis (Nichols, 2005) across the mathematical, verbal, and visuospatial ALE results. Nine clusters were identified in this conjunction analysis (**Figure 2.2D**, **Table 2.3**). These clusters included the dorsal aspect of the cingulate gyrus/SFG, as well as left dlPFC, inferior middle frontal gyri (IMFG), left aIC, and the horizontal segment of the IPS, with greater cluster extent observed in the left hemisphere. **Table 2.4** illustrates the ten top terms most associated with the core problem solving network resulting, as resulting from formal reverse inference analysis.

Table 2.3. Coordinates of convergent activation from the minimum statistic conjunction across mathematical, verbal, and visuospatial problem solving meta-analyses.

Conjunction Across Domains: Cluster Results

Cluster	Center of Mass (MNI space)			Cluster Extent (mm^3)	Mean ALE Score
	X	Y	Z		
1	2	18	48	1536	3.795
2	-36	-54	42	864	3.402
3	-28	0	56	800	3.846
4	-32	20	0	560	3.641

5	-48	28	24	120	3.229
6	-20	-70	48	96	3.411
7	26	-66	42	88	3.235
8	48	26	26	40	3.147
9	38	-48	48	32	3.251

Table 2.4. Top ten associated terms resulting from the functional decoding of the conjunction network.

Functional Decoding Analysis: Conjunction Network

	Term	Weight
1	Monitoring	17.512
2	Attention	16.065
3	Working_memory	15.302
4	Switching	14.104
5	Motor	13.421
6	Number	12.447
7	Aging	10.583
8	Memory	10.412
9	Demands	9.792
10	Attentional	9.444

2.4.7 Contrast Analyses

Then, to examine functional specialization we performed formal contrast meta-analyses (Bzdok et al., 2015; Laird et al., 2005) and identified regions of domain specificity for mathematical problem solving (**Figure 2.3A**, **Table 2.5a**), verbal problem solving (**Figure 2.3B**, **Table 2.5b**), and visuospatial problem solving (**Figure 2.3C**, **Table 2.5c**). Mathematical problem solving uniquely recruited multiple clusters within a dorsal, frontal, insular, and occipital network of regions. Superior parietal lobules, IPS, and postcentral sulci were observed bilaterally along with the left posterior precuneus and bilateral pars opercularis/IFG. The left of these IFG clusters showed significant extent along the precentral sulcal boundary towards the precentral gyrus. Mathematical-specific clusters were also observed in the bilateral anterior insula cortices, bilateral occipital poles, and in the left temporo-occipital part of the left inferior temporal gyrus. Verbal problem solving was specifically associated with convergence in a strongly left-emphasized set of frontal, temporal, and occipital areas. Large clusters occurred in Wernicke's area / left posterior temporal gyrus, Broca's area / left pars triangularis, bilateral dorsal striatum (putamen and caudate), and in the left angular gyrus. Clusters with lesser extent were observed in the left dlPFC, left lingual gyrus, and in the dorsomedial PFC. This contrast analysis revealed two additional clusters selectively observed in verbal problem solving studies in the left posterior lobe and the right anterior lobe of the cerebellum. Visuospatial problem solving studies showed domain-specific fronto-parietal convergence bilaterally in the superior frontal sulci, precentral sulci, and in right dlPFC, with cluster extent from rostral to caudal subdivisions. Visuospatial-specific clusters were additionally observed for bilateral precuneus, right inferior parietal lobule, posterior cingulate, retrosplenial cortex, and parahippocampus.

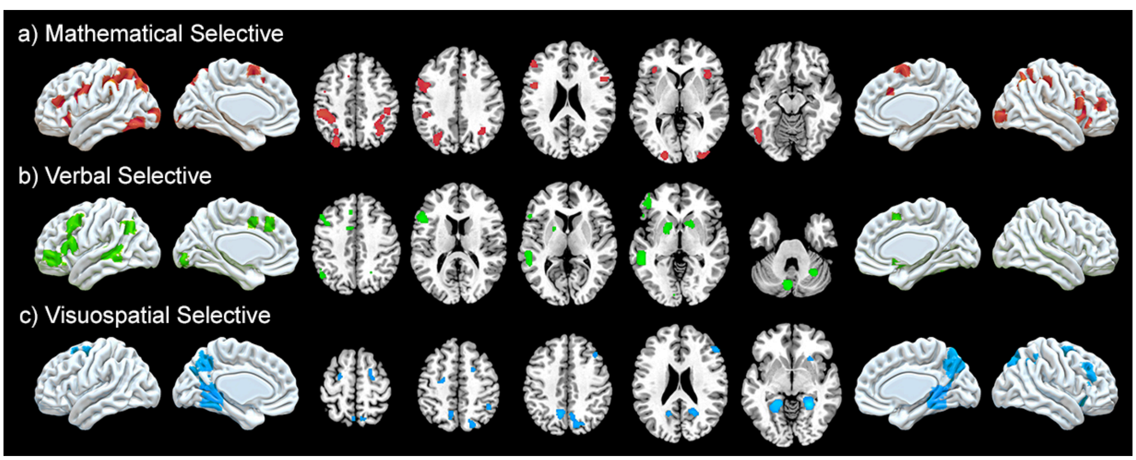


Figure 2.3. Contrast Problem Solving Meta-Analyses. Contrast analysis for (a) mathematical problem solving (*[Mathematical – Verbal]* ∩ *[Mathematical – Visuospatial]*; rose), (b) verbal problem solving (*[Verbal– Mathematical]* ∩ *[Verbal – Visuospatial]*; green), and (c) visuospatial problem solving (*[Visuospatial – Verbal]* ∩ *[Visuospatial – Mathematical]*; light blue) shows representational specificity across distinct cortical areas. The difference maps show context-bound variations across problem solving types, confirming problem solving within specific domains relies on differential sets of functionally precise neural circuitry.

Table 2.5. Coordinates of convergent activation from the contrast analyses across (a) mathematical, (b) verbal, and (c) visuospatial problem solving meta-analyses.

a) Mathematical Contrast Analysis: Cluster Results

Cluster	Center of Mass (MNI space)			Cluster Extent (mm^3)	Mean ALE Score
	X	Y	Z		
1	-36	-54	46	7128	2.341
2	36	-58	48	3560	2.347
3	-48	6	30	2120	2.028
4	-48	-66	-14	1176	2.019
5	40	20	-4	1096	2.078
6	52	14	22	1096	2.077
7	-22	-96	0	664	2.101
8	34	-94	0	528	2.134
9	-36	28	-2	504	1.951
10	-48	36	20	464	1.946
11	2	4	62	464	1.891
12	46	-32	48	424	2.093
13	40	44	16	392	1.967
14	-10	-76	54	264	1.928
15	-10	18	48	24	1.774
16	10	20	34	24	1.752
17	42	46	28	16	1.736

b) Verbal Problem Solving Meta-Analysis: Cluster Results

Cluster	Center of Mass (MNI space)			Cluster Extent (mm^3)	Mean ALE Score
	X	Y	Z		
1	-54	-38	0	2248	2.997
2	-50	20	14	1840	2.411
3	-6	-76	-32	1168	2.755
4	-18	6	-4	1016	2.473
5	-46	44	-4	928	1.908
6	16	10	-6	768	2.220
7	32	-58	-32	760	2.220
8	-44	16	42	688	1.848
9	-48	-62	38	432	2.081
10	-8	6	44	248	1.884
11	-8	28	44	216	1.807
12	-52	24	-6	80	1.819
13	24	-60	46	48	1.734
14	8	12	54	32	1.816

15	-8	-90	-4	32	1.730
16	-20	-64	48	16	1.736
17	-14	-88	-8	16	1.734

c) Visuospatial Problem Solving Meta-Analysis: Cluster Results

Cluster	Center of Mass (MNI space)			Cluster Extent (mm^3)	Mean ALE Score
	X	Y	Z		
1	-22	-48	-8	2648	2.876
2	26	-44	-8	2128	3.413
3	14	-70	44	2000	2.024
4	16	-50	10	1840	3.256
5	-14	-56	10	1408	2.716
6	-10	-60	44	1176	2.351
7	52	32	24	576	2.226
8	22	0	56	544	1.923
9	-22	-10	54	472	1.992
10	40	26	38	288	2.014
11	44	-50	50	232	1.957
12	28	20	-6	144	1.770
13	-4	-66	58	96	1.929
14	-12	-72	34	72	1.777
15	-28	16	10	48	1.747
16	-24	14	62	16	1.708

2.4.8 Problem Demand Analysis

Lastly, we wished to examine the common activation patterns associated with problem solving demand generalized across problem type. We employed a similar selection procedure to that adopted by Duncan and Owen (2000) in their observation of their multiple demand network by locating convergent neural correlates associated with task load while simultaneously controlling for variability across problem type. We selected contrasts that compared problem difficulty across different levels of identical problem tasks (see **Table A.1d**). We tested convergence across 41 Complex > Simple problem solving experiments reporting 505 foci in 21 papers and including 355 participants. Patterns of co-activation associated with problem demand were similar to common activity patterns revealed by the global, domain, and conjunction analyses. Bilateral dlPFC, dmPFC/ACC, left precentral sulcus, bilateral aIC, left lateral frontopolar cortex, left precuneus, bilateral SPL, IPL, and horizontal IPS were associated with increased problem demand (**Figure 2.4 purple**, **Table 2.6**). This problem demand network showed significant overlap with each of the within-domain meta-analytic maps, as well as with the conjunction network.

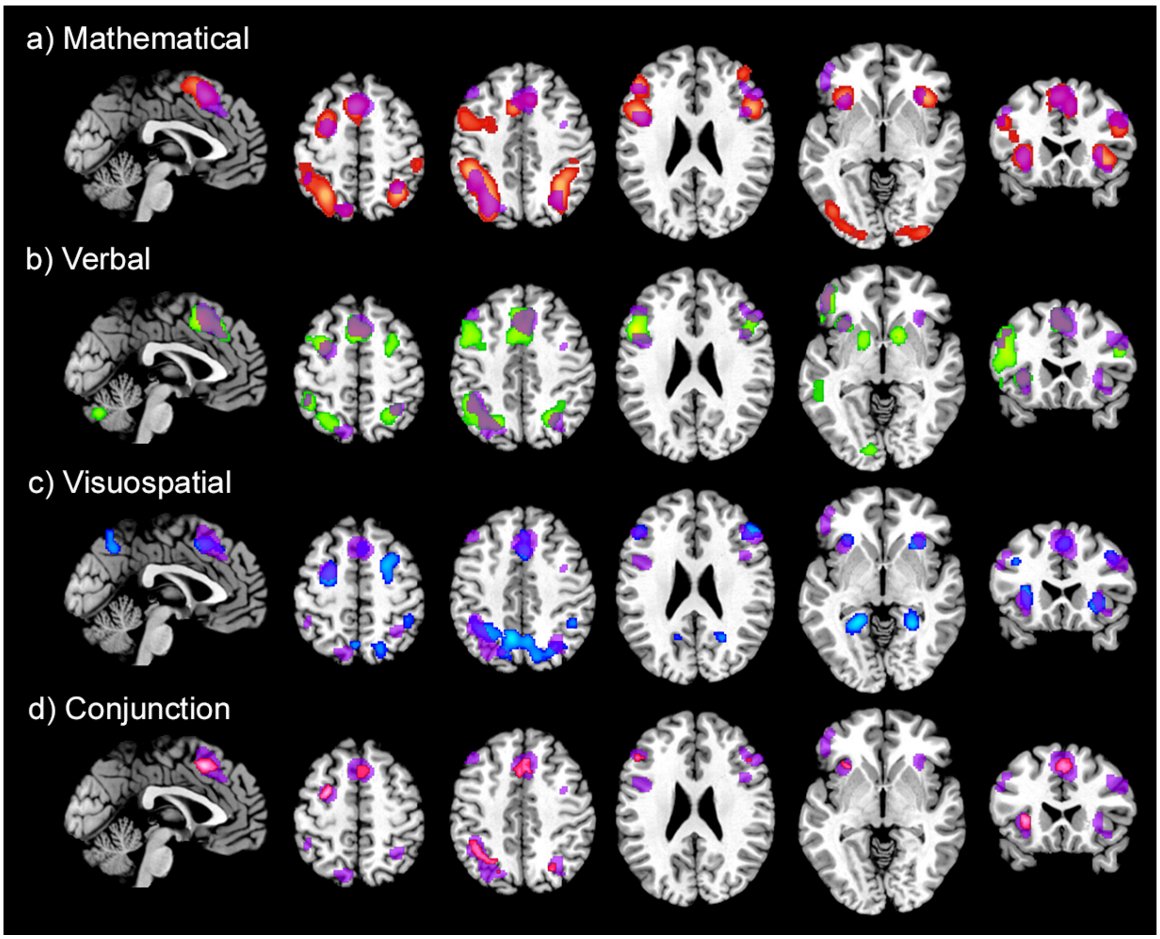


Figure 2.4. Problem Demand Meta-Analyses and Domain-Specific Overlays. High vs. low demand problem solving meta-analysis (= 41 experiments), as compared across problem solving by representational domains. Meta-analysis of problem solving tasks contrasting high vs. low demand (transparent purple) are overlaid with the three representational domain meta-analysis and the conjunction meta-analysis: (a) mathematical domain (red), (b) verbal domain (green), (c) visuospatial domain (blue), and (d) conjunction across domains (pink).

Table 2.6. Coordinates of convergent activation from the problem demand analysis.

Problem Demand Meta-Analysis: Cluster Results

Cluster	Center of Mass (MNI space)			Cluster Extent (mm^3)	Mean ALE Score
	X	Y	Z		
1	2	20	46	8000	4.666
2	46	18	30	6048	4.156
3	-30	-62	46	5888	3.863
4	-46	18	30	5488	3.903
5	-48	42	-4	2952	3.816
6	-26	-2	56	2008	4.388
7	30	-60	48	1960	3.703
8	-32	20	-2	1712	4.010
9	34	24	-6	1496	3.496

2.5 Discussion

We assessed the diverse collection of problem solving neuroimaging studies and performed multiple quantitative coordinate-based meta-analyses to identify common and distinct brain networks consistently engaged across various tasks. This study is the first to systematically explore convergent brain areas evoked by problem solving across its multiple representationally diverse forms. The meta-analytic corpus of 131 studies included paradigms that, while traditionally considered distinct, met a common operational definition of problem solving wherein participants performed multi-stepped, solution-driven critical thinking operations bounded by mathematical, verbal, or visuospatial rule sets. Global analysis across domains revealed broad involvement of frontal, parietal, insular, and occipital regions. Separate domain-specific analyses revealed consistent but unique convergent activation patterns in the dlPFC, mPFC, IPLs, aIC, and in temporal, occipital, and subcortical structures. To delineate content-general or content-specific convergence of activation, we then performed formal conjunction and contrast analyses across mathematical, verbal, and visuospatial networks. We thus identified a core system of dlPFC, dmPFC, IPS, and SPL areas that subtends all types of problem solving. Domain-specific maps revealed multiple clusters in left temporal gyrus, bilateral insula, occipital pole, bilateral pars opercularis, and areas across the superior parietal lobules that displayed functional selectivity within task sub-types. Lastly, problem demand was associated with activation across a broad set of frontal, parietal, and insular areas similar to those revealed in the domain and conjunction analyses.

2.5.1 A Core Problem Solving Network

Results from the global problem solving meta-analysis provide evidence that problem solving processes across traditionally distinct paradigms involving diverse content types engage regions within a consistent and broad network of fronto-cingulo-limbic-parietal regions. This network included frontal gyri, especially in dorsal lateral and dorsal medial PFC, anterior cingulate, parietal lobules, precuneus, occipitotemporal gyri, anterior insula, caudate, putamen, and thalamus. Of these regions, robust problem solving-related convergence was observed across principal nodes in the well-characterized central executive (Minzenberg et al., 2009; Niendam et al., 2012), Multiple Demand (Duncan, 2013, 2010, 2006; Duncan and Owen, 2000), and salience networks (Seeley et al., 2007). From a systems-level perspective of brain function, in which distinct distributed networks dynamically interact to flexibly guide complex behaviors (Cohen et al., 2004), our findings suggest generalized problem solving relies on a cooperation between perceptual and regulatory systems. Specifically, the aIC has been described as a node connecting central executive and salience networks which translates pertinent bottom-up information from sensory and limbic inputs to CEN areas, thereby negotiating network switching between internally focused (i.e., autobiographical) and externally directed (i.e., goal-oriented) states (Cocchi et al., 2013; Goulden et al., 2014; Menon and Uddin, 2010; Uddin, 2015). This interaction is thought to initiate CEN regions to implement top-down control and direct coordinated responses and behavior. Multiple areas across the PFC have been implicated in a range of broad executive functions including working memory (Curtis and D'Esposito, 2003; Owen et al., 2005), planning (Owen, 1997), flexibility (Armbruster et al., 2012; Leber et al., 2008), language comprehension (Ferstl et al., 2008), reasoning (Donoso et al., 2014; Krawczyk et al., 2011), and decision making (Keuken et al., 2014). Observed parietal CEN areas are also associated with a dorsal attention network and regions within the superior and inferior parietal lobules support a range of processes including learning (Sarma et al., 2016), visuospatial working memory (Zago and Tzourio-Mazoyer, 2002), congruency in space, time, and number sense (Riemer et al., 2016), calculation (Arsalidou and Taylor, 2011; Dehaene et al., 2003), metacognitive monitoring of information retrieval (Elman et al., 2012), and visual attention (Behrmann et al., 2004; Blankenburg et al., 2010; Duncan, 2006). The convergent activation within CEN and salience networks identified in the global problem solving analysis suggests the areas and their associated cognitive functions, as influenced by bottom-up signals mediated by aIC, play critical roles in problem solving across content domains.

While the global analysis identified common regions of convergence, domain-separated problem solving meta-analyses revealed distinct networks that, importantly, showed agreement across a focused set of frontoparietal areas. These conjunction results suggest problem solving consistently relies on a network-level subdivision of core executive regions that may bring to bear common cognitive and attentional elements fundamental to all problem solving processes. Our functional decoding analysis revealed this core network as being associated with psychologically-linked terms such as “monitoring”, “switching”, “attention”/“attentional”, “working memory”/“memory”, and “demands”, indicating the core network likely provides multiple general purpose resources including supervisory control (e.g., managerial support directing or monitoring cognition), attentional and memory processes, and perceptual and cognitive resources to achieve a broad range of problem solving tasks. One proposed role of such distributed network subdivisions is in actively managing the explicit within-network engagement of brain areas to accomplish specific actions and goals (Cole et al., 2013; Fedorenko and Thompson-Schill, 2014; Mill et al., 2017; Telesford et al., 2016). In this way, particular zones may be differentially engaged based on the demands and resources required to complete a task, and shared zones may be involved with mental operations that are critical to, and potentially transferable across, multiple task types (Cole et al., 2013; Duncan, 2010; Niendam et al., 2012). Common centralized activity across a range of tasks may also be responsible for making available basic cognitive resources, such as working memory maintenance or adaptable processing elements, that are critical in performing demanding tasks (Cabeza and Nyberg, 2000; Fuster, 2013). Indeed, these core regions are frequently functionally coupled across diverse paradigms (Duncan and Owen, 2000; Niendam et al., 2012) and likely are central in providing flexible attentional focus in many forms of human cognition (Duncan, 2013, 2006). Thus, the within-domain problem solving conjunction map engaging dmPFC, mid-DLPFC, IMFG/inferior frontal junction, left precentral gyrus, precuneus, left horizontal IPS, and bilateral areas in the SPL may represent a shared sub-network that commonly provides subordinate processing resources (e.g., those engaged in order to carry out directed cognitive tasks) as well as broader administrative support across problem solving in general. Focused parietal cortex activity, such as that observed here, has previously been implicated in start-cue processes, and dedicated sections of the dmPFC and dlPFC are believe to form a core system responsible for information maintenance, monitoring, and intentioned sustaining of goal-oriented task-sets (Dosenbach et al., 2006; Miller and Cohen, 2001). Mid-dlPFC and IMFG/IFJ regions are thought to accomplish process-relevant attentional shifting and task coordination (Brass et al., 2005; Bunge et al., 2002; Derrfuss et al., 2004). Additionally, it has been proposed that a similar set of core regions common across demanding cognitive tasks together may also act to flexibly trigger specific context-dependent schemata appropriate for task performance (Cieslik et al., 2015). These observations are consistent with the Multiple Demand system, proposed by Duncan et al. (2010, 2006; Duncan and Owen, 2000), that functions by reducing complex reasoning processes into sub-parts and engaging brain areas to carry out cognitive operations necessary for successive task steps. Thus, it is plausible that the common engagement of these multiple core CEN sub-regions during problem solving may support managerial processes involving initiating, sustaining, and directing attentional demands between multiple sub-goals that are part of inherently complex multi-stepped processes, while simultaneously providing basic cognitive resources to aid in processing within a wider set of functionally- and situationally-relevant sub-networks. Though additional empirical work should be conducted to establish definitive functional roles and mechanisms, we posit that this common network provides shared general purpose cognitive processes that commonly guide cognitive operations during problem solving to access, manage, and allocate relevant executive resources.

2.5.2 Representational Domain Specificity

The set of regions observed as common across all problem solving contrasts represents a necessary but insufficient neural system for accomplishing the demands of problem solving within particular contexts. Separate verbal, visuospatial, and mathematical meta-analyses revealed robust networks each containing regional dissociations across domains. Therefore, to better characterize domain specificities in the context of problem solving type, we performed contrast analyses examining brain function selective to each domain. Our aim was to identify any segregated areas that may be responsible for particular roles, and thereby distinguish and describe the multilevel processes occurring within context-specific problem solving.

In the case of mathematical problem solving, the explicit recruitment of fronto-parietal, occipito-temporal, intraparietal sulcal, and aIC sub-regions is consistent with accumulating evidence that a specific constellation of cortical areas is critically involved in calculation and together may act as a circuit for mathematical cognition. Numerical manipulation, number ordering, arithmetic, and magnitude processing all engage a set of such sub-areas (Ansari, 2008; Arsalidou and Taylor, 2011; Bueti and Walsh, 2009; Dehaene et al., 2003; Piazza and Eger, 2016). Moreover, the left temporo-occipital part of the inferior temporal gyrus, which was identified in this analysis, has been characterized as a “number form brain area” responsible for processing visual numerals (Grotheer et al., 2016; Merkley et al., 2016; Shum et al., 2013). The so-called triple-code model of number processing (Dehaene, 1992; Dehaene and Cohen, 1995) conceives of a ventral visual pathway that communicates numeral information from occipital poles to the number form area, where numerals are then represented in a mental scratchpad. Information is then routed along either a temporo-occipital pathway to the IPS/SPL for magnitude representation, or onto language processing areas where numbers are represented syntactically and/or fact-based knowledge is accessed. According to this model, prefrontal circuits then enact the sequential multi-stepped operations necessary for calculation. Our results coincide with this model and we posit that the contrast clusters here revealed constitute a functional sub-system to execute mathematically relevant reasoning processes.

While consensus has not yet been reached on functional pathways subtending linguistic and verbal processes in language-brain research (Poeppel and Hickok, 2004), it is clear that specific cortical areas, in line with those uncovered in the present verbal contrast analysis, play vital roles in language processing (Binder et al., 1997). Significant domain-selective convergence during verbal problem solving occurred in the classical Wernicke’s and Broca’s areas, which support a broad range of language processes (DeWitt and Rauschecker, 2013; Gough et al., 2005; Lesser et al., 1986; Poeppel et al., 2008; Wagner et al., 2001). Left-hemispheric language lateralization (Powell et al., 2006) was observed across several clusters in posterior and superior temporal sulcus/parieto-temporal junction, areas that co-activate with dorsal-stream language regions (Erickson et al., 2017) and may be responsible for verbal working memory subroutines (Poeppel and

Hickok, 2004). Additionally, this contrast also identified verbal-selectivity in the left angular gyrus, a region involved with reading comprehension and semantic processing (Seghier, 2013). Sub-cortical basal ganglia clusters (dorsal striatum/caudate) may support reasoning and decision-making (Robertson et al., 2015), linguistic computation (Monti et al., 2009; Poeppel and Hickok, 2004), and grammatical processing (Ullman, 2001). Thus, within the verbal domain, we posit that these identified regions are responsible for actualizing verbally-relevant operations as they are applied within the context of language-based problem solving.

Visuospatial-selective activity in the superior fontal sulci during problem solving topographically corresponds to the primary cortical oculomotor areas, the so-called human frontal eye fields (FEFs; Cieslik et al., 2016; Grosbras et al., 2005; Lobel et al., 2001; Vernet et al., 2014), associated with eye movements and visual awareness processes, including covert (i.e. non-motor) attention shifts during visual discrimination (Grosbras et al., 2005; Muggleton et al., 2003; Vernet et al., 2014). The observed right hemispheric visuospatially-selective MFG cluster in conjunction with the FEFs has been implicated in visual search and spatial working memory tasks (Grosbras et al., 2005). Further, as part of the brain's gaze control system, the FEFs project to PFC and parietal areas, and increased interaction of regions within this system occurs during visuospatial judgment, visual focus, and when visuospatial cognitive demands are increased (de Graaf et al., 2010; Edin et al., 2007; Vannini et al., 2004). It has been suggested that, when actively managing visuospatial working memory demands (Courtney et al., 1998), FEFs send top-down signals to PPC for visuospatial feature analysis. This analysis is then focused to task-relevant features in the visual stimuli via signals from the MFG (de Graaf et al., 2010), a finding that is consistent with our visuospatially-specific observations. These contrast results suggest that visuospatial problem solving engages a neural subsystem to allocate oculomotor and attentional capabilities for visually salient stimuli.

While these above representational domain results provide convincing evidence that distinct subsystems support problem solving within particular domains, we add a cautious note that these findings should not be interpreted as having an overly selective functional role in modality type. For example, the insula is one of the most commonly activated regions of the brain (Behrens et al., 2013; Chang et al., 2013), yet its involvement in the mathematical contrast results certainly should not be interpreted as the region exhibiting functional selectivity for mathematics. The same holds true for the within-domain maps: these results can resemble similar findings from relatively unrelated studies across the literature (e.g., the mathematical domain network shares activity within regions also observed during target detection and response inhibition, tasks which arguably have little mathematical demand; Hampshire et al., 2010). Rather, we believe our results serve to highlight the full constellation of brain regions that separately and/or cooperatively support problem solving within specific representational types.

2.5.3 Cognitive Demand in Problem Solving

The above domain-general, representational, and contrast analyses focused on identifying brain activity associated with or independent of problem type, as defined by representational modality. Included experiments spanned a diverse set of contrasts, allowing us to broadly assess convergence in neural activity linked with distinct varieties of problem solving. However, this pooling across varied contrasts simultaneously limited our ability to delineate neural correlates associated with specific cognitive processes central to problem solving. To address this limitation, we adopted the approach of Duncan and Owen (2000) and included only contrasts that clearly isolated the same aspect of problem solving, namely problem difficulty, while also controlling for task type. In this way we were able to cleanly isolate the neural activation patterns associated with cognitive demand across a breadth of problem solving tasks.

The observed clusters in the dlPFC, frontopolar cortex, dmPFC, aIC, and horizontal IPS represent the collection of brain regions that consistently respond to increases in problem demand, independent of problem type. We note that our observations are consistent with previous findings regarding the brain's multiple demand (MD) system (Camilleri et al., 2018; Duncan, 2010, 2006; Duncan and Owen, 2000; Fedorenko et al., 2013). Significant overlap was observed between the problem demand regions and each within-domain problem network. Thus, general problem solving seems to be broadly linked to the wider MD system common across diverse tasks and responsible for flexibly accomplishing multiple attentional and cognitive functions. The MD system is also thought to play a key role in focusing specific cognitive operations and interfacing with multiple brain systems to execute structured and successive goal-oriented subtasks (Duncan, 2010). It is not a particularly surprising result that a challenging problem would draw on enhanced recruitment of this MD system, but what is perhaps more insightful is that our results seem to suggest this is generally the case, regardless of the type or context of the problem task.

2.5.4 A Model for Multi-Network Cooperation in Problem Solving

Viewed collectively, these global, common, domain-specific, and demand-related results outline a set of related yet dissociable networks engaged during problem solving. The core set of activated regions appears to be centrally involved in problem demand, and formal reverse inference suggests activation across these areas provide a set of general cognitive resources that, perhaps, interface across broader brain systems and focus attention within directed sequential action (Duncan, 2010). At the same time, contrast results highlight separate representationally-specific sets of coordinated activation patterns that appear to be honed for achieving precise operations. Together, activity across these domain-general and domain-specific areas combine to form different aspects of the overall activation patterns revealed by problem solving within representational domains. Fundamentally, meta-analytic results are unequipped to evaluate such functional network dynamics, although these processes almost certainly play an essential role within problem solving. While the particular analyses we conducted cannot isolate mechanisms in how these dissociable activation patterns come together to achieve the aggregational cognitive maneuvers that make up problem solving, empirical neuroimaging studies have begun to explore these dynamics in regional functional connectivity and network interactions. Additional work is still needed to elucidate how such processes may support the large variety of problem solving processes humans face on a day-to-day basis. Here, we outline one possible interpretation of how our multiple network observations may come together to holistically achieve problem solving across diverse contexts.

We propose a speculative model of general problem solving brain function that arises from a series of sub-network and systems-level interactions that together orchestrate multifaceted cognitive procedures. In our model, the core problem solving network exerts executive control over cognitive steps to flexibly monitor and maintain neural resources. This process may involve top-down signals dispatched from the core regions to trigger and coordinate distinct subroutines adapted to domain or context-specific demands. Sub-processes that occur within broader networks, perhaps similar to those resolved by our within-domain or global analyses, would likely engage multiple whole-brain systems including salience and executive networks (Bressler and Menon, 2010). The role of these system-level interactions in problem solving may be to facilitate integrative cross-network communication, search for and detect solution relevant stimuli, and funnel information into linked sub-routines to adaptively focus attention to achieve smaller, targeted reasoning procedures accomplishing focused cognition (Cohen and D'Esposito, 2016; Duncan, 2013; Uddin, 2017). We propose that honed processes, as directed by the core network, may participate in feedback loops delivering ascending analyzed information back to whole-brain systems to sustain multi-stepped analytics and trigger confirmatory metacognitive processes (e.g., consistency checking or error detection; Mayer, 1998). If this is the case, the core network may aid in sustaining problem solving-related activity by re-dispatching or re-directing reasoning subroutines as needed, ultimately informing decision making processes to produce problem solutions. Of course, meta-analytic results alone cannot confirm this model, and a considerable amount of additional research is needed to probe the dynamic cross-network connectivity patterns we have here suggested. However, existing work that sheds light on network dynamics within problem solving, outlined below, seem to be consistent with this proposed model.

Complex network interactions such as those we have proposed here would likely take on diverse forms within problem solving, and understanding the ways in which multilevel systems share information may be key in revealing the neural basis of problem solving efficacy. In language tasks, electrocorticography has resolved dynamics across multiple left hemispheric sub-networks, and while these networks appear to coordinate with similar stepwise profiles across subjects, individual differences in response times were also reported alongside subject-by-subject variation in sub-network duration during task engagement (Collard et al., 2016). This suggests common network sequences subtend task completion, but also distinctive contributions from these dynamics may influence behavioral differences. In fact, performance in problem solving has been explicitly linked to variations in how brain systems interact across problem steps. Anderson *et al.* (2012) revealed shifting combinations of whole-brain neural sub-states in children as they solved algebra problems; individuals with high error rates utilized more sub-states at each problem step than their high-performing peers, and reliance on multiple states decreased as error-prone students achieved competency through practice. Such practice-related interactional changes have also been observed in the case of motor learning where connectivity between visual and motor systems decreased as learning occurred over time, suggesting whole-brain systems operate with increased autonomy as procedures become rote and cognitive load diminishes (Bassett et al., 2015). These findings suggest that difficulties in problem solving may be accompanied by increased cross-network complexity, perhaps as characterized by cognitive lingering or looping between unnecessary or convoluted neural states, and that ease in solution derivation may rely on more efficient multileveled network dynamics.

Yet solving truly novel problems is rarely easy, and these network dynamics should be considered in the context of problem solving as an implicitly challenging act that requires forging exploratory paths towards unknown solutions. These processes can demand substantial cognitive load and may require a certain degree of initial lingering within inefficient operations in order to flip positions of uncertainty towards coordinated and meaningful maneuvers. It is likely, then, that successful problem solving relies on a balance of multileveled and complex network crosstalk that eventually transitions towards efficient cooperation between whole-brain systems and targeted sub-processes. The use of creativity within problem solving is one resource that aids in flipping initial ineffectual processes towards productive solution derivations (Aldous, 2007; Fink et al., 2009; Lubart and Mouchiroud, 2003), and increased dynamic coupling between salience, DMN, and CEN regions has been observed to support such creative idea production (Beaty et al., 2015). At the same time, creative processes in problem solving go hand in hand with shifting attentional focus across problem features (Friedman et al., 2003; Wegbreit et al., 2012; Wiley and Jarosz, 2012), and increased effective connectivity between salience and CEN regions has been observed in individuals with a strong ability to engage in attentional switching, but not for those with reduced capacity to shift attentional stances during tasks (Kondo et al., 2004). It is likely, then, that differences in problem solving success may be characterized by the nature and process of coupling between salience, CEN, and DMN systems. Individuals experiencing difficulty in solving problems may rely on more elongated creativity and attentional shifting mechanisms that drive connectivity loops between fronto-cingulo-parietal regions. In contrast, individuals with more experience in problem solving may be better able to transition that sustained cross-system driving towards more effective honed sub-processes useful in solution derivation. Understanding the processes by which networks interact may prove to be important when understanding individual or group-level differences in problem solving competency. Meta-analytic techniques such as those employed in the present study cannot resolve brain dynamics or measure between-network connectivity, but the broad and processes-specific nature of our results suggest cooperation between large-scale brain systems and functionally specific sub-networks may play a crucial role in problem solving. Observing how these interactions occur may help elucidate remaining questions in how to better support problem solving success across individuals.

2.5.5 Limitations and Future Work

This study broadly, and for the first time, characterized the common and dissociable neural correlates underlying multiple examples of human problem solving. The investigation synthesized findings from a corpus of neuroimaging experiments reporting coordinate-based results across varied problem solving manifestations in healthy subjects. We included a wide variety of problem tasks and contrasts so that we could determine convergent brain activity associated with domain general problem solving networks. However, this approach had two main limitations. First, while this set of studies was sufficiently diverse, problem solving as a whole is widely investigated across disciplines and contexts. Thus, the mathematical, verbal, and visuospatial paradigms we examined constitute a subset of the larger breadth of human problem solving. However, while the neural substrates uncovered in this study may best model a particular slice of possible human problem solving processes, it is tenable that similar systems of coordinating perceptual, regulatory, and/or contextually bound channels are also broadly representative of generalizable neural mechanisms across the scope of human problem solving.

The second limitation stems from the diversity of contrasts chosen. We modeled problem solving as a general process by including a wide variety of contrasts. This broad focus identified commonalities across problem tasks and contexts, but simultaneously restricted our ability to resolve the differential contributions specific cognitive processes had on the resulting meta-analytic maps. However, unlike our domain-general or representationally specific results, the problem demand analysis included contrasts of only one type (i.e., complex > simple problems), and was thus able to identify such common activation patterns linked with problem difficulty. Further investigations seeking to isolate other specific constituent processes or characteristics central within problem solving can take a similar approach.

Further, all problem solving instances in this study were conducted in a laboratory environment. Yet, there is a growing cross-disciplinary appreciation of the many ways social, motivational, and affective processes can impact problem solving abilities (Beilock and Decaro, 2007; DeBellis and Goldin, 2006; Heller et al., 1992; Mayer, 1998). Thus, the mental processes underlying problem solving in a controlled setting may not identically resemble those of problem solving outside the laboratory. Additional studies bridging problem solving neuroimaging investigations with social and affective neuroscience need to be conducted before we are able to explore these topics with meta-analytic tools. Given these limitations, it is likely that the neural representations of problem solving occurring across naturalistic settings and contexts may involve different sets of activation patterns than those reported in this study. However, our finding of a shared core network that may play a role in coordinating, engaging, or negotiating sensory signals likely holds even for more distributed or complex networks. Integrating neuroimaging research in problem solving with multileveled experimental methods that explicitly attend to ecological significance may more appropriately characterize the ways affective and social factors influence the neural makeup of problem solving.

Lastly, meta-analytic results are of course limited by the quality and volume of studies available in the neuroimaging literature. There are several sources of error inherent to fMRI analyses, such as inter-subject anatomical variability and spatial smoothing, that can lead to decreased resolution in group-level fMRI analyses (Nieto-Castañón and Fedorenko, 2012), and in turn cause specious spatial overlap in meta-analytic results. This issue impacts both fMRI group-level analyses and meta-analysis in general. The results we present in this study show centralized and consistent co-activation patterns across multiple task types and domains, and because of the coherences across our set of problem solving network findings, they are not likely simply the product of sources of noise. However, spatial error may still have contributed to a lack of specificity in our observations.

This study leverages the existing wealth of problem solving activation-location findings to reveal patterns of domain-general and context-specific brain networks associated with diverse problem solving tasks. We propose that the coordinated set of these multiple systems may provide supervisory, attentional, and perceptual support to accomplish problem solving across contexts. Promising next steps in problem solving research may be to further measure these stepwise neural profiles, with an explicit consideration on how naturalistic settings and behavioral factors can impact network interactions. Previous work has linked similar brain areas as those revealed here to inter-individual variability in cognitive ability (Goodkind et al., 2015; Muller et al., 2015), but it is currently unclear how variations in network or sub-network connectivity patterns may aid or inhibit individual differences in problem solving success, and by understanding these processes from both a behavioral and neuroscientific perspective we may be better able to characterize how problem solving skills develop across training. Such insight could inform interventions to address the challenges posed by cognitive dysfunction or affective deterrents on problem solving success (Ferrari, 2011). Neuroscience-based interventions have already been used to successfully improve problem solving performance in students via mindset shifting (e.g., from intelligence-as-fixed stances to beliefs in malleable cognitive abilities; Blackwell et al., 2007; Dweck and Leggett, 1988). Such interventions have not yet been widely applied in cases of cognitive deficits, but a detailed mapping of the neural bases of problem solving could be used to develop tools and strategies to mitigate disadvantaging impacts of dyslexia or dyscalculia (Butterworth et al., 2011; Gabrieli, 2009; Kaufmann, 2008). Arguably, one of the fundamental goals of neuroimaging research as a whole is to impact and improve people's everyday experiences and behaviors. In this sense, one of the most promising future directions of neuroimaging problem solving research is to inform evidence-based educational interventions that aid in successful reasoning and skill development. Thus, understanding the neural mechanisms of problem solving, especially with a focus on how cognitive, affective, and environmental factors can influence network dynamics and neural development, has wide reaching applications.

2.6 Conclusions

In the present study, we performed multiple problem solving meta-analyses to answer the questions: "*How is content-general problem solving supported in the brain?*", *"Does a common network direct all types of problem solving processes?"*, and *"What neural underpinnings selectively represent problem solving within specific content variants?"*. By considering a comprehensive set of problem solving tasks that, heretofore, have only been considered separately, we provide evidence for a common brain-based mechanism for human problem solving in which a shared frontoparietal system provides dual attentional and regulatory support across diverse problem solving tasks, and we identify distinguishable activation patterns that may uniquely contribute to specific representationally-linked functions in problem solving across contexts. Our results suggest multiple convergent neural systems, including salience and cognitive control networks, give rise to generalized problem solving. Unique circuits within these networks support context-specific sub-classes of problem solving, and consistency across diverse stimulus modalities demonstrates a core network that supports problem solving independent of content or focus. This core network appears to play a key role in managing problem demand. The current work provides a novel neurobiological perspective on the wider study of problem solving across knowledge domains and may serve to inform neuroeducational techniques aiming to understand more about the acquisition of problem solving skills.

Chapter 3

Data Acquisition

The overall *Understanding the Neural Mechanisms of Physics Learning* project, of which the first three publications are presented in this dissertation, was designed to study functional brain changes associated with physics learning in undergraduate students before and after a semester of introductory physics (PHY 2048) at Florida International University. Chapter 3 presents the development, facilitation, and acquisition of these data.

3.1 Project Overview

As part of the *Physics Learning* project, two cohorts of students were recruited each academic year: Fall semester students underwent “pre” behavioral testing and neuroimaging scanning in August and “post” behavioral testing and fMRI scanning in December. Spring semester students underwent “pre” testing and scanning in January and “post” testing and fMRI in May. Pre- instruction fMRI sessions began the week before each regular academic session and finished before the first exams of each physics course, no more than 4 weeks into the 15-week semester. Post-instruction MRI scanning commenced immediately after final exams and concluded within 4 weeks of the mid-semester academic break (**Figure 3.1**). Each cohort included two groups of students who were enrolled in either a traditional Lecture-based class or a Modeling Instruction class.

In total, the project called for 100 students, aged 18-25, including 50 from lecture and 50 from MI classes that were enrolled across the span of six academic semesters.

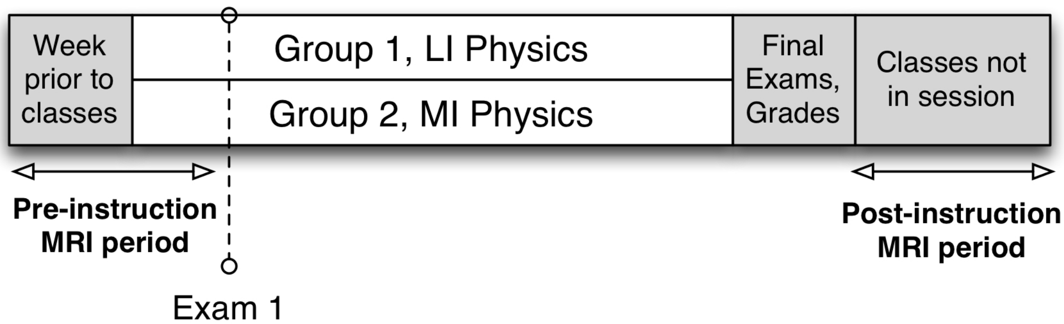


Figure 3.1. Study Design. Schematic of data collection timeline across the two study groups, Lecture Instruction (LI) and Modeling Instruction (MI).

3.2 Task Development

Three MRI paradigms were developed and/or adapted to the MRI environment as part of the overall *Understanding the Neural Mechanisms of Physics Learning* project. They were the Force Concept Inventory (FCI; (Hestenes et al., 1992)) task, the Retrieval task, and the General Reasoning task. Resting state data, in which participants engaged in task-free (e.g., mind wandering) thought while in the scanner, were also collected in addition to the three task-base paradigms. All tasks were programmed for presentation for the MRI environment using the E-Prime (Psychology Software Tools, Inc., Pittsburgh, PA) software library. Stimuli were projected from a computer located the MRI control room onto a screen placed at the back of the MRI scanner, and students viewed questions through a mirror view screen mounted to the radio frequency head coil. Participants were given a fiber optic keypad to hold in their right hand with which to respond to each question. All questions were in multiple-choice format.

3.2.1 FCI Paradigm

To probe the neural mechanisms underlying conceptual physics reasoning, we developed a scanner-adapted version of the Force Concept Inventory, which is a widely used test of physics conceptual reasoning typically given pre- and post-instruction to measure learning gains. Extensive FCI data from introductory physics classrooms show consistent significant differences between interactive vs. traditional lecture environments (Hake, 1998). The widespread use and robust interpretation of the FCI made for an ideal instrument to be adapted to the MRI environment. In addition to FCI questions, students answered high-level baseline contrast questions testing general reading comprehension. To allow for individual differences in reading comprehension, processing speeds, and physics problem solving strategies, all paradigm questions were self-paced with a maximum time per question of 45 seconds followed by 10 seconds of fixation, to allow for the brain's HRF to relax to baseline. A schematic depicting the in-scanner timing for the MRI-adapted FCI paradigm is provided in **Figure 3.2**.

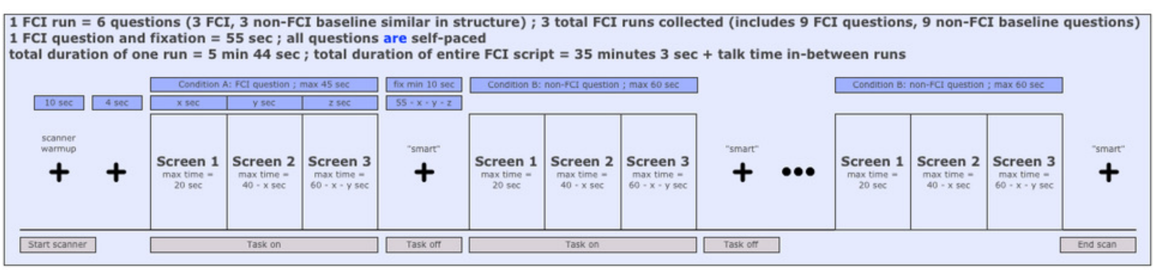


Figure 3.2. FCI Paradigm Structure. The timing and presentation of the FCI paradigm, and adapted for presentation in the MRI scanner

Force Concept Inventory problems present physical scenarios involving objects at rest or in motion. Solution derivation requires extracting meaningful and relevant information about a scene, then appropriately applying physical laws to infer causal motion or interactions between forces and objects. The FCI is typically administered as an in-class multiple-choice exam consisting of questions about intuitive, every-day scenarios. We adapted and modified parts of the paper-based FCI exam for in-scanner display to accommodate presentation and timing requirements inherent to the MRI environment. All adaptions were made to remain as true as possible to the original in-class exam, with no changes fundamentally altering any physics-related content being tested. Original FCI question text was edited for brevity, placement of visual features was standardized across questions, and items were presented in a pseudo-randomized order. To encourage participant compliance and avoid fatigue or excessive head motion, we presented a reduced exam composed of 9 items from the original test. Included items (FCI 2, 3, 6, 7, 8, 12, 14, 27, and 29) probed student understanding of Newton's 1st and 2nd laws of motion. These questions were selected to span multiple difficulty levels (34.6% to 73.6% correct rate; (Morris et al., 2012)) and because their incorrect answer options probe a diversity of non-Newtonian conceptions about physics. Additionally, technological constraints associated with the four-button MRI-compatible keypad required that we eliminate one answer option from each of the originally five-answer choice FCI items. We removed the least commonly selected answer chosen by students across all ability levels, as reported in the item response curves of (Morris et al., 2012). These answer options were 2E, 3D, 6D, 7D, 8C, 12A, 14E, 27E, and 29C, and in-scanner FCI answer options appropriately were reordered. The visual presentation of the in-scanner FCI questions, as they appeared to students in the scanner, is provided in **Figure A.1**.

In-scanner FCI and control questions were presented in a self-paced, three-phase sequence of view screens, emulating the flow of information in the original FCI exam. In the first problem initiation phase students viewed paired text and figure description a physical scenario (Phase I). Text was displayed on the top left portion of the view screen and did not exceed three sentences in length; the figure appeared at the top right portion of the view screen and depicted visual information necessary for answer making (e.g., kinematic trajectories or the spatial configuration of key features.) Students were instructed to press a keypad when they had completely read all text and felt they understood the physical scene. The button press triggered the start of the second question presentation phase (Phase II), which added a single, left-justified sentence to the middle portion of the view screen asking the student a physics question about the scenario. The student was instructed to press the keypad after fully reading the question in order to initiate the third and final answer selection phase (Phase III) wherein four possible answer choices, labeled A through D, were revealed at the bottom left of the view screen. Students were instructed to choose the correct answer and to explicitly mentally justify why the answer they selected made the most sense to them. Upon answer selection, all information on the view screen was replaced with a central fixation cross of variable duration. Variable response times per block resulted in randomized interstimulus intervals between questions.

Force Concept Inventory questions were interleaved with control questions that did not require physics reasoning or problem solving, constituting a high-level baseline comparison. Control questions displayed text and figure depictions of everyday physical scenarios and tested students on general reading comprehension and/or shape discrimination instead of physics content. Control items shared visual and linguistic characteristics to the FCI questions, containing words typically used in introductory Newtonian mechanics as well as visual presentation and self-paced timing paralleling that of the FCI problems. Text complexity for FCI and Control questions was measured using the Educational Testing Service's *TextEvaluator* tool (https://textevaluator.ets.org/textevaluator/) and no significant differences in linguistic complexity were present between conditions (total words per question: FCI = 31.4, Control = 31.3; Average words per sentence: FCI = 11.1, Control = 9.8; Syntactic complexity: FCI = 33.2, Control = 32.7; Academic Vocabulary: FCI = 22.7, Control = 32.6; Word Unfamiliarity: FCI = 36.7, Control = 32.3; Lexical Cohesion: FCI = 56.3, Control = 53.4; $p<0.05$).

3.2.2 Retrieval Paradigm

We developed a novel block-design paradigm to measure physics-based semantic memory to provide data necessary to identify whether brain networks evoked during FCI are similar to physics fact retrieval. In this paradigm, students answered questions on physics retrieval (e.g., "What is the value of the acceleration due to gravity on Earth"? with answer choices such as "9.81 $\frac{m}{s^2}$", "15 kg", "10 $liters$", "11 $\frac{ft}{s^2}$"), general retrieval (e.g., "What is the tallest mountain in the world"? with answer choices such as "Mount Rushmore", "Rainier Mountain", "Mount Everest", "Mount Logan"), and low-level baseline items (e.g., “Press a key that corresponds to the letter n” with answer choices such as “5”, “n”, “#”, “S”). A schematic of the timing for the Retrieval paradigm is provided in **Figure 3.3**.

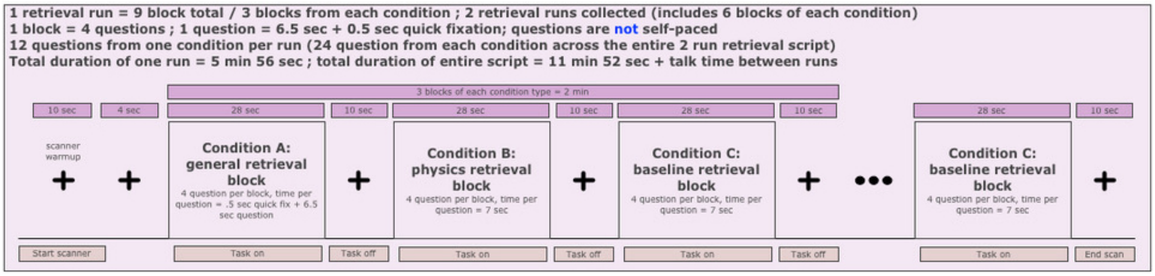


Figure 3.3. Retrieval Paradigm Structure. The structure and timing for the Retrieval paradigm

3.2.3 General Reasoning Paradigm

We adapted a fast event-related paradigm from canonical transitive inference deductive reasoning paradigms to assess general reasoning ability (Goel et al., 2009; Stollstorff et al., 2012). The task provided data necessary to identify whether brain networks evoked during the FCI are similar to reasoning outside of the domain of physics. In this task students viewed sequential relational statements (e.g., “The Fork is to the left of the Plate” and “The Fork is to the right of the Cup”) followed by a putative conclusion (e.g., “The Cup is to the left of the Plate”?). Students were instructed to indicate via button press if the conclusion logically followed from the statements. A schematic of the in-scanner timing for the General Reasoning paradigm is provided in **Figure 3.4**.

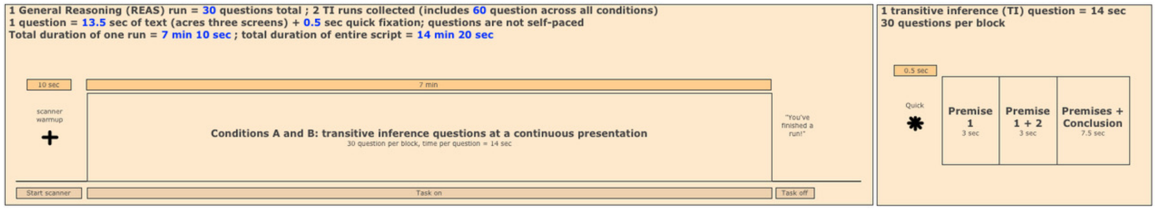


Figure 3.4. General Reasoning Paradigm Structure. The structure and timing for the General Reasoning paradigm.

3.2.4 Resting-State Paradigm

Resting state analyses examine the temporal correlation between time series of anatomically distinct brain regions when individuals engage in wakeful rest. Such measures are thought to reflect the underlying functional architecture of the brain, which is likely modulated by both behavior and experience (Cole et al., 2010; Lewis et al., 2009; van den Heuvel et al., 2009). We included a resting-state paradigm because we anticipated learning-related changes in task-based networks may accompany functional connectivity changes in the resting brain (Guidotti et al., 2015; Lewis et al., 2009; Mackey et al., 2013). Thus, we collected 12 minutes of resting state data wherein participants were instructed to lie quietly with their eyes closed in the MRI scanner and to not fall asleep.

3.2.5 Behavioral Data

In additional to fMRI data, we acquired a battery of matched pre/post behavioral assessments to aid in screening and as covariates in fMRI analyses. Participants completed an Edinburgh Handedness Inventory (Oldfield, 1971) which shows correspondence to language lateralization in the brain, the Wechsler Adult Intelligence Scale (WAIS) (Wechsler, 1958) to measure cognitive ability and generalized intelligence quotient (IQ), the Way-Finding Strategy Scale (Lawton, 1994) to measure differences in spatial anxiety and orientation strategies, the Mathematics Anxiety Rating Scale (Alexander and Martray, 1989) to measure anxiety related to calculation and performing mathematical tasks, the Science Anxiety Questionnaire (Mallow, 2006) to assess the degree to which each student experienced anxiety related to performing science tasks, the Beck Anxiety Inventory (Beck et al., 1988) as a control measure to assess the presence of generalized anxiety across study participants, a Mental Rotation Test (Shepard and Metzler, 1988; Vandenberg and Kuse, 1978) to measure student's visualization and spatial rotation abilities, a novel FCI Reasoning Survey (**Figure A.1**) to measure confidence level and overall strategy students applied within FCI problem solving, and measures on course grade earned in introductory physics classes. We included some of these measures as covariates in fMRI analyses in the present collection of work in order to explore brain-behavior correlations during physics reasoning. Additional publications are being prepared that utilize the remainder of these assessments and questionnaires.

3.3 Participant Recruitment

Participant recruitment is a consistent and common challenge across neuroimaging experiments. In general, individuals wishing to take part in neuroimaging studies initiate contact with project researchers to undergo required safety and eligibility screening, but many regularly either do not match demographic or experimental requirements, or they fail to meet metal safety, general health, neuropsychological, or certain medication restrictions. Even when participants do meet all necessary conditions they sometimes may simply no longer wish to take part in the study and withdraw from participating.

These challenges are common to all MRI experiments and across neuroimaging research institutes, and were particularly challenging due to the necessarily restrictive windows for recruitment and scanning and because of the pre/post study design requiring multiple MRI visits per student. Thus, participant recruitment and retention made up an essential and extensive portion of the project. A summary of these efforts is provided below.

The overall *Understanding the Neural Mechanisms of Physics Learning* project aimed to understand the brain-based mechanisms of physics learning and problem solving; towards this end, experiment design relied on pre- and post-instruction MRI scanning sessions. At the beginning of each academic semester, potentially eligible students were identified, contacted, screened, scheduled, and underwent MRI scanning before the conclusion of the first four weeks of university physics instruction. Because of the limited pre- and post-instruction data collection windows that were central to this study design, beginning-of-semester efforts to successfully identify and collect data from eligible participants within a short timeframe proved to be particularly challenging, yet target enrollment was ultimately achieved across three academic years and six student cohorts (**Figure 3.5**).

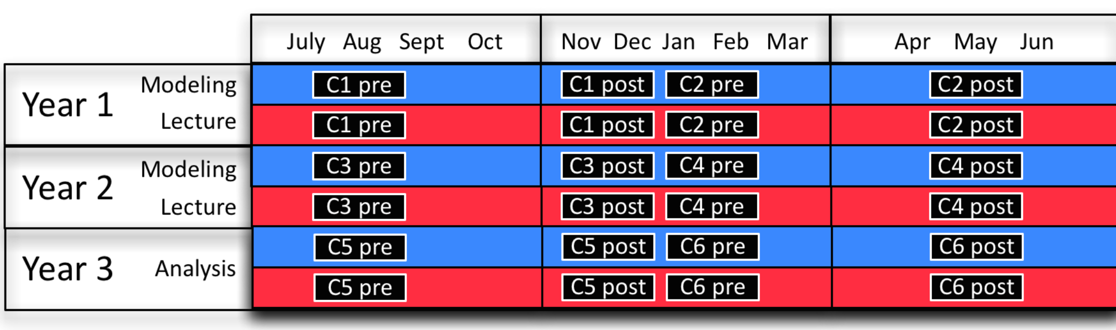


Figure 3.5. Project Timeline. "C" = Cohort; "pre" = before course; "post" = after course.

Appropriately distributing recruitment responsibilities among study researchers and lab members was essential in establishing parallel lines of facilitation across the recruitment pipeline to supporting fluid communication between interested students and the study team. Recruitment strategies included identifying and emailing potentially eligible individuals to inform them about the opportunity to participate, making multiple in-class study announcements inviting interested students to contract the research team, distributing recruitment flyers, responding to email and phone messages from interested students, reviewing Qualtrics survey responses to parse potentially eligible from ineligible participants, conducting phone calls necessary for MRI contraindications and screening, balancing student schedules with those of the MRI facility and medical staff to secure scan slots, coordinating participant reminder messages to ensure student compliance with scan schedules, managing, replenishing and distributing, participant payments from appropriate institutional channels, synchronization with the on-campus behavioral data collection team to schedule pre- and post-instruction cognitive assessments, arranging participant transportation to and from the off-campus MRI scanner (located at the University of Miami), coordinating research assistant and administrational aid necessary in conducting back-to-back data collection sessions across study participants, running MRI task training, and ultimately collecting brain data.

Across the three years of data collection, which involved managing participant recruitment, communication, scheduling, coordination, and data collection, we successfully identified and enrolled 134 total student participants (69 modeling, 65 lecture; 56 women, 78 men). However, not all enrolled participants completed their physics courses or chose to participant in both pre- and post-instruction data collection sessions. Of the 134 consented individuals, matched fMRI data sets were collected from 107 students (55 modeling, 52 traditional; 48 women, 59 men) who all successfully completed introductory physics. The enrolled study participants included 113 subjects who completed all study procedures (five pilot participants and 108 student participants), 14 subjects who were removed from the study, three who were non-responsive for post-instruction scheduling, three students who were no longer interested in participating after completing their first study visit, and one student who was unable to schedule their final visit due to scheduling conflicts. A breakdown of enrollment efforts is detailed below and outlined in **Figure 3.6**.

Years 1-3 Summary: Fall 2014 - Spring 2017

Recruitment	Multiple in-class announcements to 10 different classes 927 recruitment emails sent Study flyers distributed around campus 221 students complete the initial Qualtrics survey		
Enrollment	133 initial Qualtrics survey responses from potentially eligible students 108 completed a phone screen for neurologic a and psychiatric conditions 78 eligible to participate and screened for MRI availability 60 consented and enrolled in the study		
Data Acquisition	Year 1: 19 enrolled 1 missed appointment 1 unable to be schedule MRI 1 unresponsive after 1st session 1 incidental finding 15 matched pre/pst scans	Year 2: 49 enrolled 1 failure to disclose ineligibility 1 unsuitable for MRI 1 unresponsive at end of semester 1 unable to schedule second MRI 3 did not finish physics course 1 data corruption at second MRI 41 matched pre/post scans	Year 3: 61 enrolled 3 enrolled in ineligible course 3 self-withdrew from study 1 not suitable for MRI 2 unresponsive at end of semester 1 did not finish physics course 51 matched pre/post scans
	Total Participants to Complete Study n = 107 participants 48 female, 59 male	Total Modeling Instruction n =55 participants 22 female, 33 male	Total Lecture Instruction n = 52 participants 26 female, 26 male

Figure 3.6. Data Collection Summary. Efforts are presented across the three data acquisition years.

3.4 MRI Scanning

3.4.1 Task Training

All study participants completed a training session at an E-prime equipped computer and within a mock MRI scanner immediately prior to undergoing imaging. Training familiarized students with the MRI environment, provided instruction on how to complete all paradigms, and promoted participant compliance by providing feedback on head motion, stimuli visibility, and to answer any questions about the scan. During training, students answered example physics, retrieval, and general reasoning problems. For FCI training problems, students were instructed to read all text on the view screen completely before pressing the button to move on to the next problem solving stage. Students were not informed of the accuracy of their answers and were not guided on how to solve the physics questions. All training physics questions were adapted from FCI questions not included in the in-scanner FCI test, or from questions from a similar physics conceptual exam called the Force and Motion Concept Inventory (Thornton, 1998). A timeline of training sessions is provided in **Figure 3.7**.

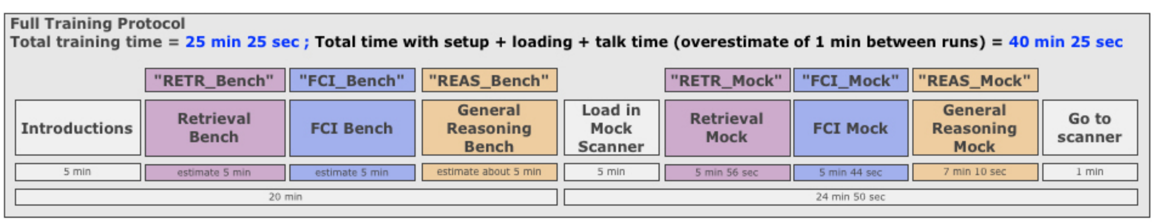


Figure 3.7. Training Protocol. Task training was performed before each MRI scanning session suing questions that were similar but not identical to the questions that were presented in the MRI scanner. The order of training tasks paralleled the order presented in the MRI scanner.

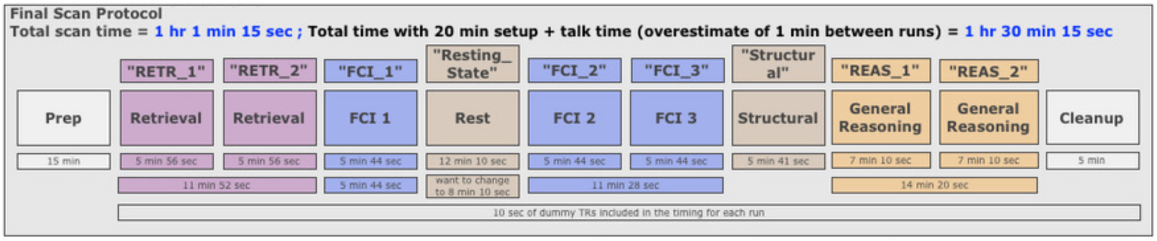


Figure 3.8. MRI Scan Protocol. MRI scanning commenced immediately after task training completion. The order and duration of all runs for all MRI paradigms are provided above.

3.4.2 fMRI Data Acquisition

Data collection for all structural and functional images was carried out on a GE Healthcare Discovery 750W 3.0T MRI scanner using a 32-channel phased-array radio frequency coil. Functional images were acquired using an gradient-echo, echo-planar sequence, with 42 interleaved slices acquired obliquely (30° from the anterior commissure/posterior commissure plane) to maximize signal in frontal regions (TR/TE = 2000/30ms, flip angle = 75°, FOV = 220x220 mm, matrix size = 64x64, voxel dimensions = 3.4×3.4×3.4 mm, slice spacing = 0 mm, with a bottom-up interleaved acquisition). For anatomical reference we acquired 3D high-resolution T1-weighted series using a 3D fast spoiled gradient recall brain volume (FSPGR BRAVO) sequence (TI = 650ms, flip angle=12°, bandwidth = 25.0kHz, voxel dimensions - 1×1×1mm, FOV=256mm, slice thickness = 1.0mm). A projector presented all visual stimuli to a screen located at the back of the MRI scanner. Response data were acquired via a fiber optic button pad that participants held in their right hand. The full MRI scan protocol, including the order and duration of all paradigms, is provided in **Figure 3.8**.

3.4.3 Post-Scan Debriefing Procedures

Immediately after training students underwent MRI scanning wherein they answered a series of physics and control questions. While in the scanner and between FCI functional runs, participants were reminded to explicitly think about why the answer their chosen answer seemed the most correct to them. Then, after exiting the scanner, students completed a written survey outlining their problem solving process for each FCI question **Figure A.1**. In the survey, students indicated the degree to which they used knowledge and reasoning to arrive at their provided answer and the degree to which they relied on a "gut feeling" to answer the question. After the scan students received compensation for their time ($50 for the first MRI scan, $100 for the second MRI scan) and, at the post-instruction session, received a photographic print out of their brain as a souvenir.

Chapter 4

Brain networks supporting physics cognition and knowledge organization in undergraduate students

4.1 Abstract

The ability to make predictions about objects and their interactions in the physical world is central to our everyday experiences. But formal physics reasoning is neither simple nor easy, and many undergraduate students invoke intuitive, but incorrect, ideas of physical causality when solving problems. Here, we used fMRI to probe physics problem-solving brain networks in 107 students after introductory college-level physics instruction. We measured sustained and sequential brain activity and functional connectivity during physics problem solving, and tested brain-behavior relationships between accuracy, difficulty, strategy, and conceptualization of physics ideas. Further, we applied module analysis to response distributions, defining groups of students who answered using similar physics conceptions, and probed for brain differences linked with different conceptual approaches. We observed integrated central executive, attentional, visual motion, and default mode brain systems that support distinct physics problem solving phases, with solution generation relying on cooperation between executive and episodic memory systems. Although accuracy alone did not impact brain function, differences in brain activity were associated with varying levels of coherence in students' physics concepts, which influenced success. Our analyses demonstrate that episodic associations

and control processes operate in tandem to support physics reasoning, offering insight into effective classroom practices to promote student success.

4.2 Significance Statement

Understanding how students learn is crucial for helping them succeed. We examined brain function during a task known to be challenging for many students – physics problem solving – to characterize underlying neural mechanisms and determine how these support comprehension and proficiency. We found integrated executive, attentional, visual motion, and default mode brain systems cooperate to achieve sequential and sustained physics-related cognition. While accuracy alone did not predict brain function, dissociable brain patterns were observed when students solved problems using different physics conceptions, and increased success was linked to conceptual coherence.

4.3 Introduction

New innovations in transforming science education to promote success and broaden participation require an understanding of how students learn. Learning interventions, both long- and short-term, yield measurable brain changes, and classroom science instruction likely influences and regulates the neural processes by which students consolidate, access, and store information (Mackey et al., 2013, 2012; van Kesteren et al., 2014). Physics in particular can be a challenging discipline for many students as it requires both a conceptual understanding and recall of physical principles, along with acquisition of procedural skills for solving problems. Evidence suggests cognition about physical concepts (e.g., velocity, acceleration, force) are encoded into specific neural representations (Mason and Just, 2016), and these representations may change during progressive stages of physics learning (Mason and Just, 2015). Problem solving is known to engage an extensive frontoparietal central executive network (CEN), both generally across domains of knowledge (Bartley et al., 2018) and specifically regarding physics concepts (Riekki et al., 2018). Collectively, these findings highlight a putative role for science education in shaping functional brain architecture and underscore the complexity of neural processes linked with proficiency in physics problem solving.

Insight into the scientific learning process may be gained by considering the obstacles students encounter. A wealth of cognitive science and education research has identified consistent patterns in how students think about physics, with a preponderance of studies focusing on difficulties mastering Newtonian mechanics (Halloun and Hestenes, 1985; McDermott, 1984; McDermott and Redish, 1999). Physics students consistently struggle to learn key concepts and novice students are known to invoke intuitive but incorrect ideas of physical causality when solving problems (Hammer, 1996a). These misleading conceptions frequently interfere with a student's ability to successfully acquire new physics knowledge (McDermott, 1991). The anterior cingulate cortex (ACC) may be engaged when students view physically causal scenes that conflict with their strongly held intuitions (Dunbar et al., 2007), yet little is known about the underlying neural processes of how students tackle conflicting physics conceptions during reasoning. These so-called "folk physics" notions (Baron-Cohen et al., 2001; diSessa, 1993; Solomon and Zaitchik, 2012) may be implicitly linked to associative memory, with naïve reasoning arising from context-based extrapolations of remembered personal experiences (McLaren et al., 2013). Alternatively, students may activate patterns of associations between knowledge elements (e.g., memories, beliefs, facts) during physics reasoning that display varying levels of coherence (integration of concepts) and robustness (applicability across contexts; (Redish, 2003)). However, such claims have not been evaluated at the neurobiological level.

We acquired functional magnetic resonance imaging (fMRI) data from 107 undergraduate students after the conclusion of a semester of university-level physics instruction. During fMRI, students were presented with questions adapted from the Force Concept Inventory (FCI; (Hestenes et al., 1992)), a widely adopted test of conceptual problem solving that presents scenarios of objects at rest or in motion and asks students to choose between a Newtonian solution and several reasonable Non-Newtonian alternatives, each of which mirror common confusions. Physics and baseline perceptual questions (**Figure 4.1**) were presented as blocks composed of three sequential phases: problem initiation, question presentation, and answer selection. Brain activity across full questions, as well as within each phase, was assessed. We then explored putative links between the neural substrates of physics problem solving and accuracy, difficulty, strategy, and student conceptualization of physics ideas. First, we probed for brain-behavior correlations revealed by parametric modulation of the BOLD signal in *a priori* reasoning and memory-linked regions of interest (ROIs; **Figure 4.2a**) located in the left dorsolateral prefrontal cortex (dlPFC), ACC, left posterior parietal cortex (PPC), left hippocampus, and retrosplenial cortex (RSC), and across the whole brain. Second, because student response patterns across FCI questions are heterogeneous and even incorrect answer choices provide meaningful information about students' conceptions (Savinainen and Scott, 2002), we distinguished sub-types of "physics thinkers" based on their FCI answer choices. Specifically, we applied community detection to FCI answer distributions to identify sub-groups of similarly responding students and contrasted brain activity between groups to examine differential ways of thinking about the behavior of physical phenomena.

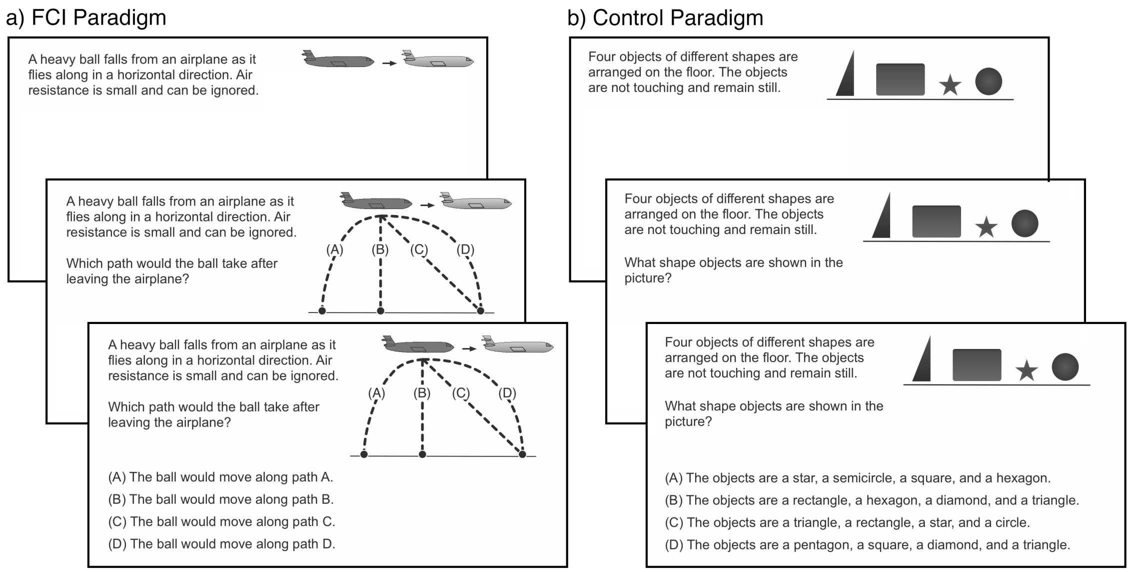


Figure 4.1. In-Scanner FCI Paradigm. Three-phase sequential progression of an exemplar in-scanner (a) Force Concept Inventory (FCI) question and (b) Control question.

4.4 Materials and Methods

4.4.1 Participants

One hundred and seven healthy right-handed participants who took part in this study were undergraduate students enrolled in introductory calculus-based physics at Florida International University in Miami, Florida (age 18-25 years; mean: 20.2, SD: 1.39; 48 women). Study participants were selected from a large set of applicants (N=496, from 22 different physics course sections) who responded to in-class recruitment announcements made at the beginning of the academic semester. Participants were free of cognitive impairments, neurological and psychiatric conditions, did not use psychotropic medications (i.e. stimulants, anti-anxiety/anti-depressants, recreational drugs), and had never previously completed a university-level physics course. Of the 107 individuals who underwent post-instruction MRI scanning, 11 were college freshmen, 51 were sophomores, 32 were juniors, and 13 were seniors. The introductory physics course emphasized problem-solving skill development and covered topics in Newtonian mechanics, including motion along straight lines and in two and three dimensions, Newton's laws of motion, work and energy, momentum and collisions, and rotational dynamics. MRI scans commenced immediately after the completion of the physics courses final exam and concluded no more than two weeks after the end of the academic semester. Written informed consent was provided prior to participating in the study in accordance with Institutional Review Board approval and students received monetary compensation for their time.

4.4.2 FCI Task

The Force Concept Inventory, a widely used (Von Korff et al., 2016) and reliable (Lasry et al., 2011) test of conceptual understanding in Newtonian Physics (Hestenes et al., 1992), that includes a series of questions about physical scenarios was adapted for the MRI environment. FCI questions do not require mathematical calculation; rather they force students to choose between a correct answer and multiple commonsense alternatives. The task included three phases: participants viewed a figure and descriptive text presenting a physical scenario (Phase I), a physics question was presented (Phase II), and participants viewed four possible answers and were instructed to choose the correct answer and mentally justify why their solution made the most sense (Phase III). Participants provided a self-paced button press to advance between phases and provide their final answer; a fixation cross was shown after answer selection before presentation of the next scenario. Question blocks were of maximum duration 45s and were followed by a fixation cross of minimum duration 10s. Control questions presented everyday physical scenarios and queried students on general reading comprehension instead of physics content. Control questions also included three phases (Control I, Control II, and Control III) to match the presentation of FCI questions.

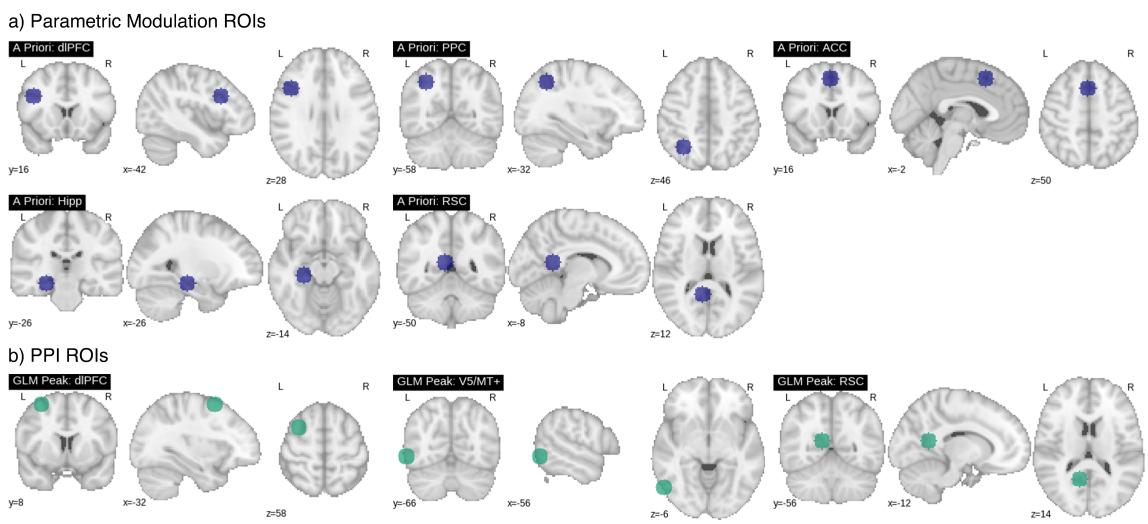


Figure 4.2. Regions of Interest. a) The hypothesis-driven ROIs (blue) selected from coordinate results of problem solving (dlPFC, PPC, and ACC; (Bartley et al., 2018)) and episodic, spatial, and declarative memory (hippocampus and RSC; (Andrews-Hanna et al., 2014; Robinson et al., 2015)) meta-analyses. b) The seeds selected for further exploration of task-based functional connectivity via psychophysiological interaction analysis (PPI; green). These regions were derived from peak group-level results from the FCI > Control (all phases) contrast.

4.4.3 FCI Problem Difficulty and Post-Scan Strategy Questionnaire

Post-scan debriefing included a paper-based questionnaire in which students rated the degree to which they had used "knowledge and reasoning" or had relied on a "gut feeling" to solve each FCI question. Normative question difficulty was measured as the percent of students who answered incorrectly on FCI questions from a dataset of more than 4,500 student responses to the FCI administered at Harvard University, Mississippi State University, and Rice University and reported in (Morris et al., 2012). Problem solving strategy was measured as a self-reported measure assessed immediately after scan completion. Students were given a post-scan, written questionnaire depicting each in-scanner FCI question with the statements "*I used knowledge and reasoning to arrive at my answer*" and "*I relied on a 'gut feeling' to arrive at my answer*" (**Figure A.1**). Students rated their agreement/disagreement with each statement for each FCI question on a 5-point Likert scale.

4.4.4 fMRI Acquisition and Pre-Processing

Functional images were acquired on a GE 3T Healthcare Discovery 750W scanner with an interleaved gradient-echo, echo planar imaging (EPI) sequence (TR/TE = 2000/30ms, flip angle = 75°, FOV = 220x220mm, matrix size = 64x64, voxel dimensions = 3.4×3.4×3.4mm, 42 axial oblique slices, 172 volumes/run × 3 runs). A T1-weighted series was acquired using a 3D fast spoiled gradient recall brain volume (FSPGR BRAVO) sequence with 186 contiguous sagittal slices (TI = 650ms, bandwidth = 25.0kHz, flip angle = 12°, FOV = 256x256mm, and slice thickness = 1.0mm). Pre-processing was performed using tools from the FSL (www.fmrib.ox.ac.uk/fsl) and AFNI (http://afni.nimh.nih.gov/afni) software libraries. To allow for image intensity stabilization, the first five frames of each functional run were discarded. All functional and structural images were aligned to a common stereotactic origin and spatial orientation to match that of the MNI152 template. Rigid-body motion correction was performed on functional runs by aligning all images in each run to the middle volume. Anatomical and functional images were skull stripped, functional images were high-pass filtered (110s), and a 12-degree-of-freedom affine transformation was applied to co-register the series with each participant's structural volume. Non-linear resampling was applied to transform all images into MNI152 2mm space and functional volumes were spatially smoothed using a 5mm Gaussian kernel. Additionally, all motion-corrected non-registered 4D data underwent visual inspection and TRs associated with visually identified motion artifacts were flagged for exclusion in further analysis and their corresponding FD values were recorded. The minimum of the distribution of these artifact-linked FDs was used as a common scrubbing threshold across subjects during analyses. TRs with excessive motion (including one frame before and two frames after) were scrubbed if they met or exceeded a threshold of 0.35mm FD (Power et al., 2011). Runs containing excessive motion (≥33% of within-block motion) were discarded from the analysis, resulting in the omission of three runs from two individuals. Six motion parameters (translations and rotations) were included as nuisance regressors in all analyses.

4.4.5 General Linear Model Analyses

Stimulus timing files were created for each participant based on question phase onset/offset times. FCI and control questions were modeled as blocks from question onset to the onset of a concluding fixation cross triggered by answer selection. The contrast FCI > Control was modeled across full question duration; three additional GLM analyses were performed for the individual phases. Timing files were convolved with a Gamma-modeled hemodynamic response function and the first temporal derivative of each convolved regressor was included in analyses to account for any offsets in peak BOLD response. General linear modeling for within- and between-subject analyses was performed in FSL using FEAT. Group-level activation maps for the contrasts FCI > Control, Phase I > Control I, Phase II > Control II, and Phase III > Control III were thresholded with a cluster defining threshold (CDT) of $P < 0.001$ and a cluster extent threshold (CET) of $P < 0.05$ (FWE corrected). Meta-analytic functional decoding for the FCI > Control, Phase I > Control I, Phase II > Control II, and Phase III > Control III contrasts was performed on the resulting unthresholded z-statistic maps with a 200-topic GC-LDA (Rubin et al., 2016) topic model trained on the Neurosynth database (Yarkoni et al., 2011).

4.4.6 Task-Based Functional Connectivity Analysis

We tested for psychophysiological interaction (PPI) effects associated with the FCI task across three seeds modeled as 10mm spheres and centered on peaks from the overall FCI > Control map located in the left V5/MT+, left dlPFC, and RSC (**Figure 4.2b**). ROIs were transformed into native space and time series were extracted from unsmoothed data and included as regressors in separate within-subject PPI analyses performed on spatially smoothed 4D data sets. Design matrices for the within-subject PPI analyses contained regressors for the ROI time series, the condition difference vector modeling the differences between FCI and Control timing files, a vector representing the sum of the FCI and Control conditions, and the interaction between the task difference vector and ROI time series. The interaction term was calculated by zero-centering the task explanatory variable, and the mean of the ROI time series was set to zero. All task and interaction regressors, but not the ROI time series, were convolved with a Gamma-modeled hemodynamic response. PPI analyses were carried out separately for each ROI and resultant beta maps were averaged within-subject and carried into three separate group-level analyses. ROI-to-voxel task-based functional connectivity analyses were thresholded at a significance of $P < 0.001$ CDT, $P < 0.05$ CET (FWE corrected).

4.4.8 Definitions of *A Priori* Regions of Interest and PPI Seeds

Five *a priori* regions of interest (ROIs) were selected for inspection of potential physics problem solving-related brain activity correlations with problem solving strategy, accuracy, and difficulty. ROIs were meta-analytically defined to include areas associated with *problem-solving* (e.g., left dorsolateral prefrontal cortex (dlPFC), ACC, left posterior parietal cortex (PPC; (Bartley et al., 2018)) and *episodic and spatial memory* (e.g., left hippocampus and retrosplenial cortex (RSC); (Andrews-Hanna et al., 2014; Robinson et al., 2015)). A recent meta-analysis on problem-solving revealed the left dlPFC, the left PPC, and the ACC as critically involved in problem solving involving mathematical, visual, or verbal stimuli (Bartley et al., 2018). Centroid meta-analytic coordinates from these regions were used as seeds in the present analysis. In addition, to investigate to putative connection between memory-related processes during physics problem-solving and behavioral measures, we selected two functionally-relevant ROIs from memory neuroimaging literature in the left hippocampus and RSC to explore potential involvement long-term and episodic memory retrieval plays within physics reasoning. These two regions were chosen to investigate the role long-term memory and/or autobiographical memory, especially when involving spatial thinking, may have on behavioral measures during physics problem-solving. For the hippocampal seed, a region was chosen the left middle hippocampus based on connectivity-based parcellation findings suggesting this region is particularly involved in declarative memory (Robinson et al., 2015). The RSC seed was drawn from peak coordinates from meta-analytic results on the neural correlates on autobiographical memory (Andrews-Hanna et al., 2014). In that study, the RSC was identified as a region simultaneously present within a core autobiographical memory network, as well as particularly involved in memory retrieval of events characterized by spatial context and visuospatial processing. The five ROIs were modeled as 10mm spherical seeds (**Figure 4.2a**). Solving physics problems relies on deduction and knowledge recall; thus, we hypothesized that the fMRI signal in the problem-solving and hippocampus ROIs would parametrically increase with problem difficulty and reasoning strategy. Specifically, we expected difficulty to modulate activity in ACC and dlPFC and reasoning strategy to modulate activity in ACC, dlPFC, PPC, and hippocampus. If students reported using physical intuition (i.e., they answered via a *"gut feeling"*), we expected a positive parametric effect in RSC, an area linked to visualization and memory of autobiographical experiences (Vann et al., 2009). Additionally, due to the influence of strongly held yet non-physical conceptions on confidence bias in introductory Newtonian mechanics (Potgieter et al., 2010), we did not expect accuracy-related parametric effects to be present in any ROI.

4.4.7 Brain-Behavior Correlates

Separate within-subject parametric modulation analyses were performed for accuracy, difficulty, and self-reported problem-solving strategy. All parametric modulator analyses contained identical design matrices to those of the FCI > Control (all phases) subject-level analyses but included a parametric modulator regressor wherein question duration was modeled by student-specific FCI > Control response times and regressor heights were modulated by question-specific accuracy, self-reported strategy (as assessed by post-scan strategy questionnaires), and question difficulty. Accuracy was modeled with regressor heights of 1, 0, or -1 corresponding to correct, no response, or incorrect answer provided. Difficulty was measured as a normative miss rate per FCI question, as measured externally (Morris et al., 2012). Problem-solving strategy was measured on a Likert scale by a post-scan questionnaire (**Figure A.1**). In this way, accuracy and problem solving strategy were subject-specific measures and question difficulty was modeled externally as a normative metric of how challenging (% incorrect) each FCI question generally is for introductory physics students, as measured across a large body (>4,500) of university students who had taken the exam. If any parametric modulator had zero variance within a run (i.e., the student reported using an identical strategy for all questions, or they answered all questions either correctly or incorrectly) then the run was discarded to avoid rank deficiency in the design matrix. Resulting beta maps were then averaged across within-subject runs.

Brain-behavior correlations were tested via two separate analyses In the first analysis we extracted within-subject parametric modulator beta values within the five hypothesis-driven ROIs (**Figure 4.2a**) and conducted one sample t-tests on the beta distributions to test for significant variations from baseline. In this first analysis we tested the hypotheses that 1) fMRI signal in the ACC and the left dlPFC would parametrically increase with problem difficulty, that 2) signal in the ACC, dlPFC, PPC, and hippocampus ROIs would parametrically increase with reasoning strategy (i.e., they answered using *"knowledge and reasoning"*), that 3) fMRI signal in the RSC would parametrically increase if students reported using physical intuition (i.e., they answered via a *"gut feeling"*), and that 4) no accuracy-related parametric effects would be present in any ROI.

In the second analysis, whole-brain beta maps resulting from the parametric modulation GLMs were averaged across groups to determine if significant network-level activity, outside that of any selected hypothesis driven ROIs, was present during problem solving associated with the behavioral measures. Group-level analyses were performed with whole-brain beta maps resulting from the parametric modulation GLMs to determine if significant network-level activity was present during problem solving associated with the behavioral measures. Meta-analytic functional decoding was performed for significant whole-brain results on the resulting unthresholded whole-brain z-statistic maps with a 200-topic GC-LDA (Rubin et al., 2016) topic model trained on the Neurosynth database.

4.4.9 Description of Conceptual Modules and How They Were Computed

Recent work has identified distinct communities of non-Newtonian FCI answer choices given by frequency of co-occurring student responses to the original FCI exam (Brewe et al., 2016). These so-called "conceptual modules" represent dissociable incorrect physics conceptions that students commonly hold **Table 4.1**. The present analysis made use of these conceptual modules to detect group differences in how students approached within-scanner FCI questions (see §4.4.10 Student Response Profiles). The set of these previously derived conceptual modules and how they were computed are outlined below. Full details on these findings and their interpretations can be found in (Brewe et al., 2016).

The original creators of the FCI described a taxonomy of "misconceptions" probed by their test and provide a list of FCI answer choices that they believed indicated the presence of these incorrect physics beliefs (Hestenes et al., 1992). Brewe *et al.* (2016) sought a more data-driven approach towards identifying conceptually linked sets of incorrect FCI answer choices and their associated underlying physical interpretations. To do this they applied a community detection algorithm to a large set of FCI student responses and identified nine conceptual modules representing dissociable incorrect physics conceptions present in the FCI. Similar communities to those Brewe *et al*. (2016) described have been separately identified and analogously interpreted via factor analysis in other investigations (Scott et al., 2012; Scott and Schumayer, 2017), and many of the conceptions they described parallel those discussed in related work on naïve physics ideas and the conceptual difficulties students face in Newtonian physics (Clement, 1983;

diSessa, 1993; McDermott, 1984) According to the characterizations of Brewe *et al.* (2016), some conceptual modules appear to represent coherent sets of student's physics conceptions while others may be more consistent with a "knowledge-in-pieces" view of student physics thinking (Andrea A. diSessa, 1983). The presence of coherent non-Newtonian conceptions in the FCI has been observed in previous findings (Savinainen and Viiri, 2008; Scott et al., 2012; Scott and Schumayer, 2017) and is consistent with the notion that students often hold highly integrated, yet incorrect, collections of physical conceptions that they apply across diverse contexts (Hammer, 1996a; Redish, 2003)). Such coherent knowledge structures are frequently referred to as mental models. In contrast, when student's incorrectly reason through physics problems by way of drawing upon physics ideas that are more loosely connected, the knowledge structures are said to be more fragmented (Andrea A. diSessa, 1983; diSessa, 1993; Hammer, 1996b; Redish, 2003). Students who rely on less coherently organized knowledge structures such as these tend to have a difficult time applying the same knowledge across contexts and situations (Redish, 2003).

Brewe *et al.*'s (2016) conceptual modules were identified through a process of treating student FCI answer responses as a bipartite network represented as a Students X Responses matrix. This matrix was then multiplied by its transpose to project the bipartite network into a Responses X Responses matrix, which was weighted by the number of students choosing each answer pair. So for example, assuming three students choose answer A on FCI question 2, and two of these three students chose answer C on FCI question 3 with the third student choosing D on FCI question 3, then the answer projection of the bipartite network would be an edge with weight 2 between answers 2A and 3C and a edge with weight 1 between answers 2A and 3D. At this point, the answer projection network represents the network of responses, but it is too densely connected to analyze. Backboning or sparsifying the network is a process that aims to reduce the number of edges by retaining only the 'important' edges while preserving as many connected nodes as possible. In order to sparsify this network, the researchers used a locally adaptive non-parametric sparsification (LANS) algorithm (Foti et al., 2011) which works with non-parametric distributions. A community detection algorithm (InfoMap R; D. Edler and M. Rosvall, The MapEquation software package, available online at http://www.mapequation.org; (Rosvall and Bergstrom, 2008)) was then applied to sparsified network to identify groups of responses that are more commonly connected together than to the rest of the network.

Table 4.1. Conceptual modules, their constituent FCI answer choices, and their descriptions. Bolded FCI answer choices represent the items that we adapted for in-scanner presentation. In cases where (Brewe et al., 2016) did not describe student conceptualizations associated with a module, we have provided additional interpretations that add/expand upon the original descriptions to aid in interpretation of outcomes in the present study. Modules that we have elaborated upon are marked with an obelisk †. Additionally, where appropriate we provide external references that describe further observations of the common incorrect physical conceptions detailed by a conceptual module.

Common Non-Newtonian Conceptual Modules (Brewe et al., 2016)

	Module	Constituent FCI Answer Choices	Detailed Conceptual Description
m1	Moving objects experience an "impetus" force	**2B**, **3B**, 5E, **6A**, **7A**, **7E**, **8D**, 8E, 13C, **14A**, **14C**, 17D, 18E, 19B, 20A, 21A, 22D, 23D, 23E, 24C, 24D, 25A, 25B, 25E, 26A, **27B**, 30E	If an object is moving, then there must be a force actively causing the motion. This fictional force is referred to as an "impetus" force. Students who hold this view may also believe that, if an object's motion becomes diminished, a diminishing impetus force must have caused the change. This (incorrect) Galilean model was held by many medieval physicists and is often characterized by a common confusion among students between the concepts of force and velocity. The impetus force fallacy is a prevalent, particularly coherent, and persistent model that students' usually apply across contextually diverse situations

			(Hammer, 1996b; Savinainen and Viiri, 2008).
m2	More force yields more result	1A, **2C**, 2E, **3E**, 4A, 10C, 11E, 15C, 19C, 20E, 21D, 26B, 26C, 26D, **27D**, 28D, 30A	If a force acts on an object and is increased, then *something* about the object’s motion must also increase. This idea is correct if the increased quantity is acceleration. However, students holding this view often assign the increased quantity incorrectly and/or without justification (e.g., displacement, time, velocity, or an additional non-physical force). Similarly, how the quantity increases (e.g., constantly or scaled by a factor) is often assigned incorrectly and/or without justification. Because of the vague/unstructured nature of what quantity increases and how, this module is applied in different and sometimes conflicting ways depending on the problem or context. This module is compatible with the physics phenomenological primitive, or *p-prim*, known as “Ohm’s p-prim” (diSessa, 1993). P-prims are irreducible, loosely connected sets of intuitive physics knowledge that students use to explain physical phenomena (diSessa, 1993). Ohm’s p-prim asserts that how much result something receives is proportional to the amount of resistance it gives (more effort implies more result and more resistance implies less result). In contrast to more stable and consistent sets of physics ideas, such as those describe in *m1*, p-prims such as the one paralleled in this module illustrate more fragmentary intuitive knowledge pieces that describes contextually situated emergent knowledge that student’s use when reasoning (Hammer, 1996b).
m3	Competing forces cause motion, or acceleration and velocity are not distinguished	4D, **6C**, 11B, 16C, 17A, 20B, 20C, 25D, 28C	This module is described by two competing interpretations: 1) competing forces cause motion (e.g., motion occurs because one force “wins” out over another competing force), and/or 2) students fail to discriminate between velocity and acceleration, thus a net force yields a velocity.
m4	A moving object’s impetus eventually “runs out”[†]	5D, **8E**, 10D, 11C, 15D, 16D, 18D	This module is likely a variant of the impetus force module (*m1*). However, the ways in which this module varies from *m1* is not specified in the original paper (Brewe et al., 2016). We interpret this module as representing an impetus conception of force wherein a moving objects’ impetus force “runs out” over time. This is characterized by the belief that objects have a natural tendency to remain still. That is, students who hold this view may believe objects set in motion by an active agent stores the external force as it moves, but then releases its impetus over time due to a natural tendency of all objects to remain inactive.

m5	Confusion in relating an object's speed and path†	5C, 9C, **12C**, **12D**, 13B, 18C, 19A, 22C, **27A**	This module is less consistent, and therefore less characterized by concrete, coherent non-physical beliefs. In (Brewe et al., 2016), the module is described as indicating an indistinct lack of understanding about velocity. We further characterize it here as students reaching an incorrect conclusion that involves relating a moving object's path to its speed. However, the way in which students relate path to speed is not applied consistently, indicating students do not have a clear strategy and may be confused.
m6	A sudden force on an object induces an instantaneous path change	**7C**, **8A**, 9B, 15E, 16E, 17E, 21B, 23C, 28A	The module is characterized by the belief that when a moving object undergoes a quick change in force it will instantaneously (e.g., over an infinitesimally small time interval) alter its path to move in the direction of the external force.
m7	An object's mass determines how it falls	1D, **2D**, 9D, 10E, 18A, 19D, 23A	The incorrect belief that objects of different masses fall at different rates and traverse different horizontal distances as they fall. This view is frequently compatible with the Aristotelian view of falling bodies wherein more massive objects fall faster, although there is evidence that student's naïve conceptions about how mass relates to trajectory don't share the same coherence as Aristotle's description (Whitaker, 1983). FCI answer choices in this module suggest students may view this supposed mass to time of flight/distance relationship as not linearly related. This module may be an iteration of the *more force yields more result* module (*m2*).
m8	Indistinct confusion regarding downward force or scenario description†	**14B**, 21C, 22A, **29D**	This model was originally proposed as reflecting student confusion with interpreting the physical scenario described in a particular FCI question (Brewe et al., 2016). However, because the module is composed of answer choices not related to a single FCI question, we have extended this interpretation to describe an indistinct confusion about either the scenario descriptions or downward force. Two answer choices in this module (21C, 22A) indicate students may be confused about the physical scenario described in one FCI question (in particular the length of time a force is applied to an object). An additional item (29D) indicates students believe air exerts a dominant downward force on objects, while another item (14B) indicates students believe objects fall vertically even after being released with an initial horizontal velocity. Thus, this module involves disjoint ideas that are difficult to characterize as a single coherent conceptual structure. We interpret it as involving unidentifiable confusions about force and/or the physical description of a question.

m9	Confusion regarding gravitational action†	1B, **3A**, 5A, 11A, 28B, 29C, 30B	Multiple answer items in this set (1B, 3A, 5A, 11A, 30B) share a focus on the gravitational force as acting in replacement of, or dominant to other forces. Thus, the module is described in terms of gravity as being a constant factor in each incorrect answer (Brewe et al., 2016). We additionally observe that this confusion about gravitational action appears to impact how students predict resulting motion or itemize which forces act on moving and/or stationary objects. How gravity impacts motion and/or free body diagrams differs from answer to answer, indicating this module may represent somewhat inconsistent ideas about gravity.

4.4.10 Student Response Profiles

Given evidence indicating student responses to the FCI provide insight into how students think about physics problems (Savinainen and Scott, 2002), we performed a module analysis, similar to that in Brewe *et al.* (2016), of the observed FCI answer distributions to identify student response profiles. The data were treated as a bipartite matrix of Students x Responses. This bipartite matrix was computed and then projected into a weighted adjacency matrix of students, $A = MM^T$, where M is the bipartite matrix. Each element in A represents the count of how many times one student agreed with any other student (values from 0 to 9, for 9 questions). Next, we performed nonparametric sparsification on A (Foti et al., 2011) to identify the backbone of the graph. Backboning identifies important links within a network and reduces the number of spurious links. A significance value was computed for each edge weight and the edge weights were thresholded at $P < 0.01$. We performed community detection (InfoMap R; (Rosvall and Bergstrom, 2008)) on the backbone network to identify sub-groups of students who provided similar responses to the FCI prompts. We then assessed the scaled within-group overlap of incorrect FCI responses across a set of nine previously measured physics modules consisting of jointly selected incorrect FCI response items ((Brewe et al., 2016); **Table 4.1**). Each group's relative conceptual module representation was scaled by group size to allow for comparisons across groups of different sizes. Alignment with conceptual modules indicates students draw on specific non-Newtonian physics conceptions. Finally, we tested for network differences across student groups. An omnibus test was conducted for the FCI > Control contrast as well as for the three whole-brain PPI maps. Significant F-test results were further interrogated with *post hoc* t-tests across groups. Maps were thresholded at $P < 0.001$ CDT, $P < 0.05$ CET (FWE corrected).

4.4.11 Data Availability

A GitHub repository was created at http://github.com/nbclab/PhysicsLearning/FCI to archive the source files for this study, including the e-Prime stimulus files, data analysis processing scripts, behavioral data, statistical brain images, and module analysis files.

4.5 Results

4.5.1 Physics problem solving engages visual motion, central executive, and default mode processes

FCI responses (mean accuracy = 61%, mean response time (RT) = 20.2s) were consistent with previous reports (Lasry et al., 2013; Savinainen and Scott, 2002) and significantly differed ($p<0.001$) from control responses (mean accuracy = 98%, mean RT = 15.8s), suggesting overall task compliance. Maps of FCI > Control blocks revealed activation across a fronto-temporo-parietal network, including the prefrontal cortex (PFC), left dorsal striatum, PPC, RSC, and dorsal posterior cingulate cortex, lateral occipitotemporal cortex (V5/MT+), and cerebellum (**Figure 4.3a**; **Table 4.2**). To tease apart constituent neural processes, we analyzed sequential phases of the problem-solving process and observed multiple dissociable whole-brain networks linked with problem initiation (Phase I), question presentation (Phase II), and answer selection (Phase III). Phase I was associated with a similar activity pattern as the FCI > Control contrast, Phase II maps were characterized by right-emphasized dorsal posterior parietal and V5/MT+ engagement, and Phase III maps included medial anterior and posterior nodes of the default mode network (DMN; **Figure 4.3b-d**; **Table 4.3**). These network transitions from fronto-temporo-parietal (Phase I) to dorsal attention (DAN; Phase II) followed by default mode cooperation (Phase III) elucidates the important role V5-DMN-CEN interactions may have within physics reasoning processes. Meta-analytic functional decoding was performed on the resulting unthresholded z-statistic maps using Neurosynth (Rubin et al., 2016), indicating that switching, default mode, motion perception, and reasoning processes underlie physics problem solving (**Figure 4.3** radar plots; **Table 4.4**).

Decoding sequential phases indicated problem initiation may reflect visuospatial attention, perceptual/motor, and memory retrieval; question presentation was associated with switching, visual short-term memory, and numbers, and answer selection was linked to DMN-related terms (e.g., unconstrained (free), mentalizing, and ambiguous), consistent with mental exploration of a solution. Next, to assess information exchange across GLM-identified regions during problem solving, we performed task-based functional connectivity (FC) analyses for three seeds centered on peaks of the overall FCI > Control map located in the left V5/MT+, the left dlPFC, and the RSC. Psychophysiological interaction (PPI) results (**Figure 4.4**; **Table 4.5**) revealed greater physics problem solving-related coupling (relative to control conditions) of the left V5/MT+ with DAN brain areas, the left dlPFC with V5/MT+ and DMN areas, and the RSC with frontoparietal, DMN, and salience network (SN) regions. These outcomes suggest complex visual information may be carried through a dorsal stream to frontoparietal regions that direct CEN-DMN network exchanges during physics reasoning.

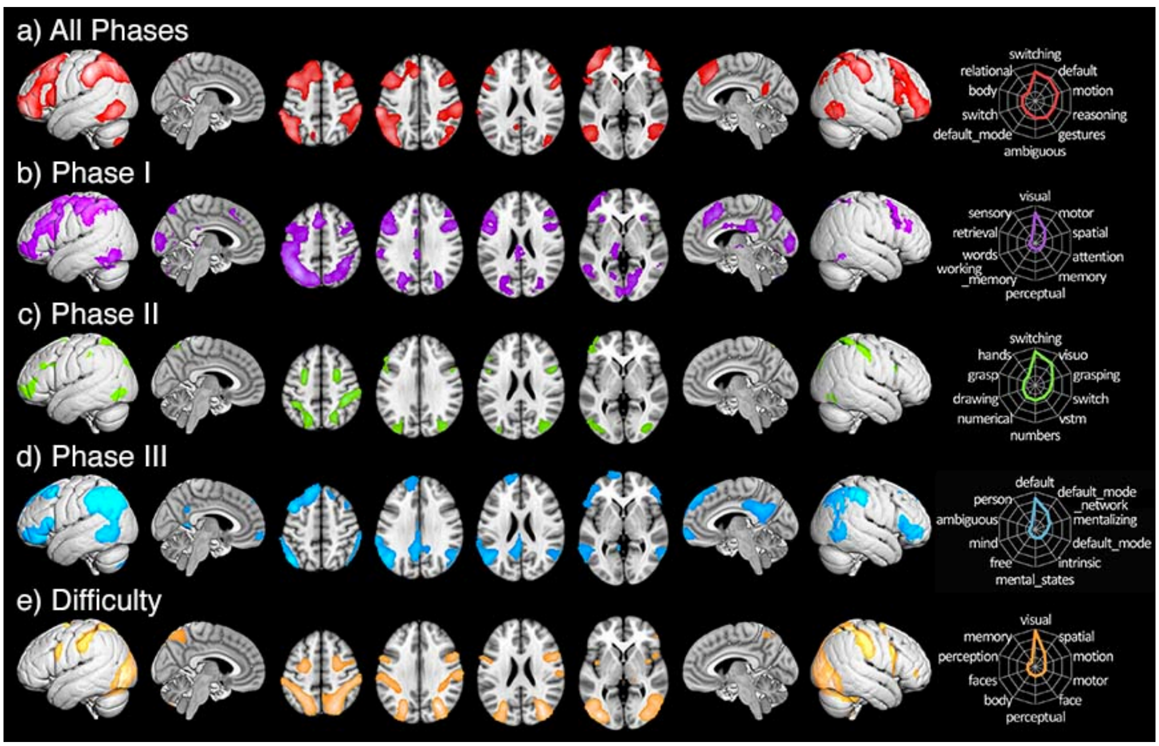


Figure 4.3. Physics Problem Solving-Related Brain Activation. Activation of FCI > Control for a) problem solving across all phases, b-d) across each sequential problem phase, and e) parametric modulation across all phases by problem difficulty. Adjacent radar plots depict functional decoding results of the top ten weighted terms for each network.

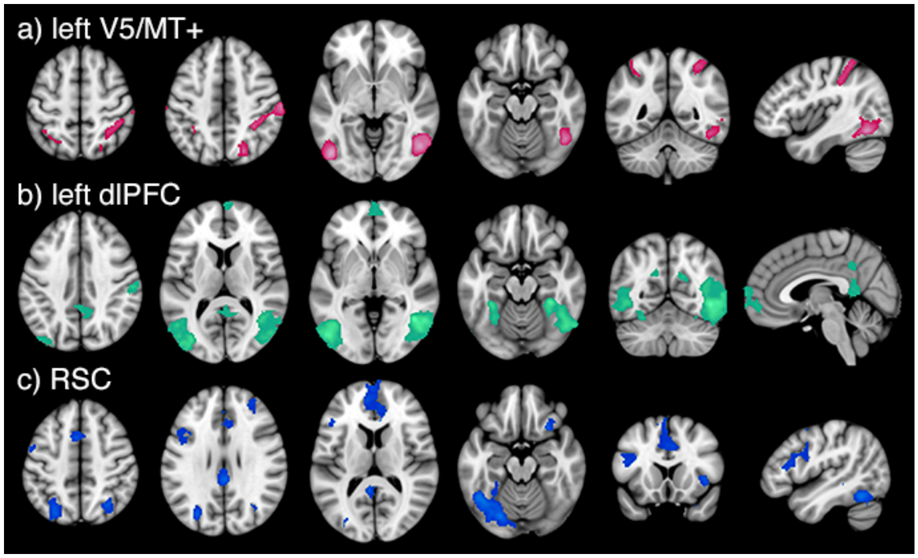


Figure 4.4. Physics Problem Solving-Related Functional Brain Connectivity. Whole-brain PPI task-based functional connectivity associated with FCI > Control for a) left V5/MT+, b) left dlPFC, and c) RSC seeds.

Table 4.2. Center of mass activation coordinates for the FCI > Control contrast as reported in MNI space. Cluster region labels are based off those reported by the IBASPM116 Human Brain Atlas.

Cluster	Hemisphere	Center of Mass (MNI space)			Cluster Extent (mm^3)	Mean Z Score	Region Labels
		X	Y	Z			
1	B	-34	30	26	85072	5.676	Frontal_Mid_L, Frontal_Sup_L, Frontal_Inf_Tri_L, Frontal_Sup_Medial_L, Precentral_L, Frontal_Inf_Oper_L, Frontal_Inf_Orb_L, Frontal_Mid_Orb_L, Supp_Motor_Area_L, Frontal_Sup_Orb_L, Frontal_Mid_Orb_L, Rolandic_Oper_L, Cingulum_Mid_L, Cingulum_Ant_L, Frontal_Sup_Medial_R, Supp_Motor_Area_R, Temporal_Pole_Sup_L
2	R	50	-50	26	57088	5.222	Temporal_Inf_R, SupraMarginal_R, Parietal_Inf_R, Temporal_Mid_R, Occipital_Mid_R, Parietal_Sup_R, Angular_R, Postcentral_R, Occipital_Inf_R, Fusiform_R,

							Precuneus_R, Cerebellum_Crus1_R, Occipital_Sup_R, Cerebellum_6_R
3	L	-46	-54	42	49632	6.386	Parietal_Inf_L, Angular_L, SupraMarginal_L, Parietal_Sup_L, Occipital_Mid_L, Precuneus_L, Postcentral_L, Occipital_Sup_L, Temporal_Sup_L, Temporal_Mid_L
4	R	46	28	18	36576	4.746	Frontal_Mid_R, Frontal_Inf_Tri_R, Frontal_Inf_Oper_R, Frontal_Mid_Orb_R, Frontal_Inf_Orb_R, Frontal_Sup_R, Precentral_R, Rolandic_Oper_R, Insula_R
5	L	-54	-58	-8	17864	5.243	Temporal_Inf_L, Temporal_Mid_L, Occipital_Inf_L, Occipital_Mid_L, Cerebellum_Crus1_L
6	R	28	-70	-44	13744	5.257	No label generated
7	L	-32	-74	-52	6120	4.148	No label generated
8	L	-8	-56	16	1680	3.666	Precuneus_L, Calcarine_L, Cingulum_Post_L, Cuneus_L
9	L	-12	10	8	1392	3.997	Caudate_L

Table 4.3. Center of mass activation coordinates for the contrasts (a) FCI Phase I > Control Phase I, (b) FCI Phase II > Control Phase II, and (c) FCI Phase III > Control Phase III as reported in MNI space. Cluster region labels are based off those reported by the IBASPM116 Human Brain Atlas.

a) FCI Phase I > Control Phase I

Cluster	Hemisphere	Center of Mass (MNI space)			Cluster Extent (mm^3)	Mean Z Score	Labels
		X	Y	Z			
1	B	-16	-46	24	295832	4.570	Precentral_L, Parietal_Inf_L, Occipital_Mid_L, Postcentral_L, Frontal_Inf_Tri_L, Frontal_Mid_L, Lingual_R, Calcarine_R, Parietal_Sup_L, Occipital_Mid_R, Calcarine_L, Temporal_Inf_L, Precuneus_L, Parietal_Sup_R, Frontal_Inf_Oper_L, Occipital_Sup_L, Temporal_Mid_L, Parietal_Inf_R, Supp_Motor_Area_L, Lingual_L, Frontal_Sup_L, Cerebelum_Crus1_L, Cerebelum_Crus1_R, Angular_L, SupraMarginal_L, Precuneus_R, Occipital_Sup_R, Fusiform_L, Cerebelum_6_R, Angular_R,

							Frontal_Sup_Medial_L, Cuneus_R, Occipital_Inf_L, SupraMarginal_R, Cuneus_L, Fusiform_R, Cerebelum_6_L, Cerebelum_Crus2_R, Frontal_Inf_Orb_L, Cerebelum_Crus2_L, Frontal_Mid_Orb_L, Insula_L, Cerebelum_8_R, Postcentral_R, Supp_Motor_Area_R, Rolandic_Oper_L, Cerebelum_7b_R, Cingulum_Mid_L, Cerebelum_7b_L, Frontal_Sup_Medial_R, Cerebelum_9_R, Cingulum_Mid_R, Cerebelum_4_5_R, Cerebelum_8_L, Occipital_Inf_R, Vermis_7, Cingulum_Ant_L, Vermis_8, Frontal_Sup_Orb_L, Vermis_6, Temporal_Mid_R, Temporal_Sup_L, Vermis_4_5
2	R	42	12	36	26408	3.970	Frontal_Mid_R, Frontal_Inf_Oper_R, Frontal_Inf_Tri_R, Precentral_R, Frontal_Sup_R, Rolandic_Oper_R
3	R	56	-54	-16	11680	4.148	Temporal_Inf_R, Temporal_Mid_R, Cerebelum_Crus1_R, Fusiform_R, Occipital_Inf_R
4	B	-10	-24	-4	11048	3.788	Thalamus_L, Hippocampus_L, ParaHippocampal_L, Lingual_L, Thalamus_R, Precuneus_L, Cerebelum_4_5_L, Vermis_3, Pallidum_L, Amygdala_L
5	B	-4	-26	26	5664	3.862	Cingulum_Post_L, Cingulum_Mid_L, Precuneus_L, Cingulum_Ant_L, Cingulum_Mid_R, Calcarine_L
6	R	34	24	-8	2280	4.186	Insula_R, Frontal_Inf_Orb_R
7	L	-32	-72	-60	1408	3.814	
b) FCI Phase II < Control Phase II							
1	R	40	-56	32	43064	4.630	Occipital_Mid_R, Parietal_Sup_R, Temporal_Inf_R, Postcentral_R, Parietal_Inf_R, SupraMarginal_R, Occipital_Inf_R, Precuneus_R, Fusiform_R, Occipital_Sup_R, Temporal_Mid_R, Angular_R, Cerebelum_Crus1_R, Cerebelum_6_R
2	L	-34	-64	32	30072	4.405	Occipital_Mid_L, Parietal_Sup_L, Parietal_Inf_L, Occipital_Inf_L, Precuneus_L, Temporal_Inf_L, SupraMarginal_L, Occipital_Sup_L, Temporal_Mid_L, Postcentral_L, Angular_L
3	L	-26	-2	54	8344	5.003	Frontal_Mid_L, Frontal_Sup_L,

							Precentral_L
4	L	-48	40	4	6760	3.888	Frontal_Inf_Tri_L, Frontal_Inf_Orb_L, Frontal_Mid_Orb_L, Frontal_Mid_L
5	R	26	-2	52	6528	4.770	Frontal_Sup_R, Frontal_Mid_R, Precentral_R
6	R	52	10	20	3168	4.3639	Frontal_Inf_Oper_R, Precentral_R, Rolandic_Oper_R, Frontal_Inf_Tri_R
7	L	-50	6	20	1464	3.670	Frontal_Inf_Oper_L, Precentral_L, Rolandic_Oper_L
c) FCI Phase III < Control Phase III							
1	L	-54	-56	26	50152	5.606	Temporal_Mid_L, Angular_L, Parietal_Inf_L, SupraMarginal_L, Occipital_Mid_L, Temporal_Inf_L, Temporal_Sup_L, Parietal_Sup_L, Occipital_Inf_L
2	B	-14	42	32	50128	4.809	Frontal_Sup_L, Frontal_Sup_Medial_L, Frontal_Mid_L, Frontal_Mid_Orb_L, Frontal_Sup_Medial_R, Frontal_Mid_Orb_R, Supp_Motor_Area_L, Frontal_Sup_R, Frontal_Sup_Orb_L, Precentral_L, Rectus_L, Frontal_Sup_Orb_R, Rectus_R, Frontal_Mid_Orb_L, Supp_Motor_Area_R, Frontal_Inf_Oper_L
3	R	58	-54	26	27744	4.478	Angular_R, Temporal_Mid_R, SupraMarginal_R, Parietal_Inf_R, Temporal_Inf_R, Occipital_Mid_R, Temporal_Sup_R, Postcentral_R
4	L	-48	36	-10	21792	4.617	Frontal_Inf_Orb_L, Frontal_Inf_Tri_L, Frontal_Mid_Orb_L, Frontal_Inf_Oper_L, Frontal_Mid_L, Temporal_Pole_Sup_L
5	B	-4	-48	26	20344	4.496	Precuneus_L, Cingulum_Post_L, Cingulum_Mid_L, Cuneus_L, Cingulum_Post_R, Precuneus_R, Cingulum_Mid_R, Calcarine_L, Cerebelum_4_5_L, Lingual_L, Vermis_4_5, Cingulum_Ant_L
6	R	28	-78	-44	11680	4.961	
7	R	54	34	-4	10160	3.929	Frontal_Inf_Tri_R, Frontal_Inf_Orb_R, Frontal_Inf_Oper_R, Frontal_Mid_Orb_R, Frontal_Mid_R
8	L	-30	-80	-50	5560	3.823	
9	L	-12	10	12	1240	3.877	Caudate_L
10	L	-14	-8	18	64	3.214	Caudate_L, Thalamus_L

Table 4.4. Meta-analytic functional decoding for unthresholded z-statistic (a) FCI > Control (all phases), (b) FCI Phase I > Control Phase I, (c) FCI Phase II > Control Phase II, (d) FCI Phase III > Control Phase III, and (e) problem difficulty modulator maps. Decoding was performed with a 200-topic GC-LDA (Rubin et al., 2016) topic model trained on the Neurosynth database. The top ten terms returned are provided along with their associated Neurosynth correlation values.

a) Full Questions	
Term	**Weight**
switching	309.71084
default	276.1635173
motion	252.5753468
reasoning	214.5672386
gestures	211.2976516
ambiguous	180.1752178
default_mode	147.8986879
switch	137.3589833
body	135.9365735
relational	117.1724557
b) Phase I: Problem Initiation	
Term	**Weight**
visual	6280.671847
motor	3552.329718
spatial	2180.073879
attention	1794.573378
memory	1503.498075
perceptual	1334.731314
working_memory	1212.675255
words	1171.632954
retrieval	1047.038397
sensory	1044.932068
c) Phase II: Question Presentation	
Term	**Weight**
switching	174.7799387
visuo	143.0582605
grasping	95.3737437
switch	83.24127548
vstm	80.24913636
numbers	80.15246068
numerical	78.16072276
drawing	68.03863533
grasp	63.52682393
hands	62.93979874
d) Phase III: Answer Selection	
Term	**Weight**
default	649.6765185
default_mode_network	447.7949888
mentalizing	329.1184083
default_mode	240.3050669

intrinsic	215.4858992
mental_states	186.8147481
seed	150.9431503
free	124.7647576
mind	121.8747808
ambiguous	111.3774804
e) Difficulty Modulator	
Term	**Weight**
visual	4998.611373
spatial	2165.71031
motion	1454.923421
motor	1451.786037
face	1361.697261
perceptual	1270.365251
body	1211.229165
faces	1162.215922
perception	1046.94595
memory	785.0733801

Table 4.5. Center of mass coordinates for psychophysiological interaction (PPI) task-based functional connectivity between (a) V5/MT+ , (b) dlPFC, and (c) RSC, and seeds associated with the contrast FCI > Control, as reported in MNI space. Cluster region labels are based off those reported by the IBASPM116 Human Brain Atlas.

a) Left V5/MT+ Seed							
Cluster	Hemisphere	Center of Mass (MNI space)			Cluster Extent (mm^3)	Mean Z Score	Labels
		X	Y	Z			
1	R	54	-30	40	14128	4.104	SupraMarginal_R, Postcentral_R, Parietal_Inf_R, Parietal_Sup_R, Rolandic_Oper_R
2	R	50	-62	-8	11176	4.334	Temporal_Inf_R, Temporal_Mid_R, Occipital_Inf_R, Fusiform_R, Occipital_Mid_R
3	L	-48	-72	-2	5344	4.131	Occipital_Mid_L, Occipital_Inf_L, Temporal_Mid_L, Temporal_Inf_L
4	R	24	-70	46	2216	3.607	Occipital_Sup_R, Parietal_Sup_R, Precuneus_R, Occipital_Mid_R, Angular_R, Cuneus_R
5	L	-60	-24	34	1776	3.386	SupraMarginal_L, Parietal_Inf_L, Postcentral_L
6	L	-32	-54	54	1256	3.369	Parietal_Inf_L, Parietal_Sup_L
b) Left dlPFC Seed							
1	R	46	-60	0	39504	4.181	Temporal_Mid_R, Temporal_Inf_R, Occipital_Mid_R, Fusiform_R,

							Occipital_Inf_R, Cerebelum_Crus1_R, Temporal_Sup_R, Cerebelum_4_5_R, Angular_R, Cerebelum_6_R, SupraMarginal_R, ParaHippocampal_R
2	L	-44	-72	4	28432	4.200	Occipital_Mid_L, Temporal_Mid_L, Fusiform_L, Occipital_Inf_L, Temporal_Inf_L, Cerebelum_6_L, Angular_L, Cerebelum_4_5_L, Parietal_Inf_L
3	B	4	-50	24	8096	3.489	Precuneus_R, Precuneus_L, Cingulum_Post_L, Cingulum_Mid_R, Cingulum_Post_R, Cingulum_Mid_L, Vermis_4_5, Calcarine_R, Cuneus_L, Cuneus_R, Lingual_R
4	B	4	62	-2	4168	3.517	Frontal_Sup_Medial_R, Frontal_Mid_Orb_L, Frontal_Mid_Orb_R, Frontal_Sup_Medial_L, Frontal_Sup_R
5	R	58	-24	40	1672	3.631	SupraMarginal_R, Postcentral_R
c) Left RSC Seed							
1	B	0	36	22	23072	3.727	Frontal_Sup_Medial_L, Supp_Motor_Area_L, Cingulum_Ant_R, Cingulum_Ant_L, Frontal_Mid_Orb_R, Frontal_Sup_Medial_R, Cingulum_Mid_R, Frontal_Mid_Orb_L, Cingulum_Mid_L, Supp_Motor_Area_R, Frontal_Sup_L, Rectus_R
2	L	-32	-64	-18	12432	3.972	Fusiform_L, Cerebelum_6_L, Cerebelum_Crus1_L, Lingual_L, Temporal_Inf_L, Occipital_Inf_L, Cerebelum_4_5_L, Calcarine_L
3	L	-28	-70	36	7952	4.007	Occipital_Mid_L, Parietal_Sup_L, Parietal_Inf_L, Occipital_Sup_L, Angular_L
4	L	-44	12	26	4512	3.499	Frontal_Inf_Tri_L, Precentral_L, Frontal_Inf_Oper_L, Postcentral_L, Rolandic_Oper_L
5	B	0	-34	28	3832	3.708	Cingulum_Mid_L, Cingulum_Post_L, Cingulum_Mid_R, Cingulum_Post_R
6	L	-56	-32	-6	3480	3.798	Temporal_Mid_L
7	R	30	-64	44	2816	3.588	Angular_R, Parietal_Sup_R, Occipital_Sup_R, Occipital_Mid_R, Parietal_Inf_R
8	R	30	44	26	1944	3.563	Frontal_Mid_R, Frontal_Sup_R
9	R	38	16	-2	1296	3.620	Insula_R, Frontal_Inf_Orb_R, Frontal_Inf_Oper_R
10	B	-2	-50	10	1104	3.570	Precuneus_L, Cingulum_Post_L, Vermis_4_5, Cingulum_Post_R,

							Calcarine_L, Lingual_L
11	R	30	22	-20	1104	3.654	Frontal_Inf_Orb_R, Insula_R, Temporal_Pole_Sup_R, Temporal_Pole_Mid_R

4.5.2 Difficulty, but not accuracy and strategy, modulate brain activity during problem solving

To relate brain function to behavioral measures impacting student success, we tested our hypotheses that activity in meta-analytically derived ROIs (e.g., left dlPFC, left PPC, ACC, left hippocampus, and RSC) would be parametrically modulated by student-reported strategy and normative problem difficulty (Morris et al., 2012), but not answer accuracy. Brain-behavior correlations were tested via two separate analyses. In the first analysis we extracted within-subject parametric modulator beta values from the five hypothesis-driven ROIs and conducted one sample t-tests to determine if 1) fMRI signal in the ACC and the left dlPFC as parametrically increased with problem difficulty, 2) signal in the ACC, dlPFC, PPC, and hippocampus was parametrically increased with reasoning strategy, 3) signal in the RSC parametrically increased when students reported using physical intuition, and 4) no accuracy-related parametric effects were present in any ROI. No significant variations in BOLD signal from baselines were observed within the ROIs tested. Beta distributions across all ROIs are shown in **Figure 4.5**. While no significant BOLD signal modulations were observed in these *a priori* ROIs, the second exploratory whole-brain parametric modulation analysis revealed DAN and occipital activity were positively modulated by problem difficulty (**Figure 4.3e**; **Table 4.6**). This indicates that the physics reasoning network is consistently activated regardless of whether or not a correct answer is achieved and does not reflect students' perception of their reasoning strategy. Importantly, the most salient relation appears to be between degree of difficulty and engagement of brain regions linked with visuospatial perceptual, memory, and attentional processes, as assessed by functional decoding (**Figure 4.3e right**) suggesting that memory-guided spatial or motion perception and visualization may be especially taxed when problem difficulty is increased.

Table 4.6. Activation coordinates associated with the whole-brain parametric modulation of the FCI > Control (all phases) contrast by normative problem difficulty, as reported in MNI space. Cluster region labels are based off those reported by the IBASPM116 Human Brain Atlas.

Whole-Brain Activity Correlated with Problem Difficulty

Cluster	Hemisphere	Center of Mass (MNI space)			Cluster Extent (mm^3)	Mean Z Score	Labels
		X	Y	Z			
1	B	38	-60	16	118720	5.750	Occipital_Mid_R, Fusiform_R, Parietal_Sup_R, Temporal_Inf_R, Temporal_Mid_R, Cerebelum_6_R, SupraMarginal_R, Precuneus_R, Postcentral_R, Occipital_Inf_R, Occipital_Sup_R, Parietal_Inf_R, Cerebelum_Crus1_R, Angular_R, Cerebelum_4_5_R, Cuneus_R, Lingual_R, Calcarine_R, ParaHippocampal_R, Rolandic_Oper_R, Cerebelum_Crus2_R, Precuneus_L
2	L	-36	-62	16	95296	5.539	Occipital_Mid_L, Parietal_Inf_L, Parietal_Sup_L, Fusiform_L, Occipital_Inf_L, Cerebelum_6_L, Temporal_Inf_L, Cerebelum_Crus1_L, Occipital_Sup_L, SupraMarginal_L, Temporal_Mid_L, Precuneus_L, Postcentral_L, Cerebelum_8_L, Cerebelum_9_L, Cerebelum_4_5_L, Cerebelum_Crus2_L, Angular_L, Cerebelum_7b_L, Lingual_L, Cuneus_L
3	R	40	4	34	21960	4.593	Precentral_R, Frontal_Inf_Oper_R, Frontal_Sup_R, Frontal_Mid_R,

							Insula_R, Rolandic_Oper_R, Frontal_Inf_Tri_R, Putamen_R, Supp_Motor_Area_R, Temporal_Pole_Sup_R
4	L	-26	-6	54	7560	4.714	Precentral_L, Frontal_Sup_L, Frontal_Mid_L, Supp_Motor_Area_L
5	L	-20	-72	-56	3104	4.079	
6	L	-54	4	28	2848	4.192	Precentral_L, Frontal_Inf_Oper_L, Rolandic_Oper_L
7	R	22	-48	-58	2760	3.873	
8	R	46	38	6	1752	3.721	Frontal_Inf_Tri_R, Frontal_Mid_R
9	L	-40	-2	6	1352	4.289	Insula_L, Rolandic_Oper_L
10	R	18	-30	-6	848	3.440	Thalamus_R, ParaHippocampal_R, Hippocampus_R, Lingual_R

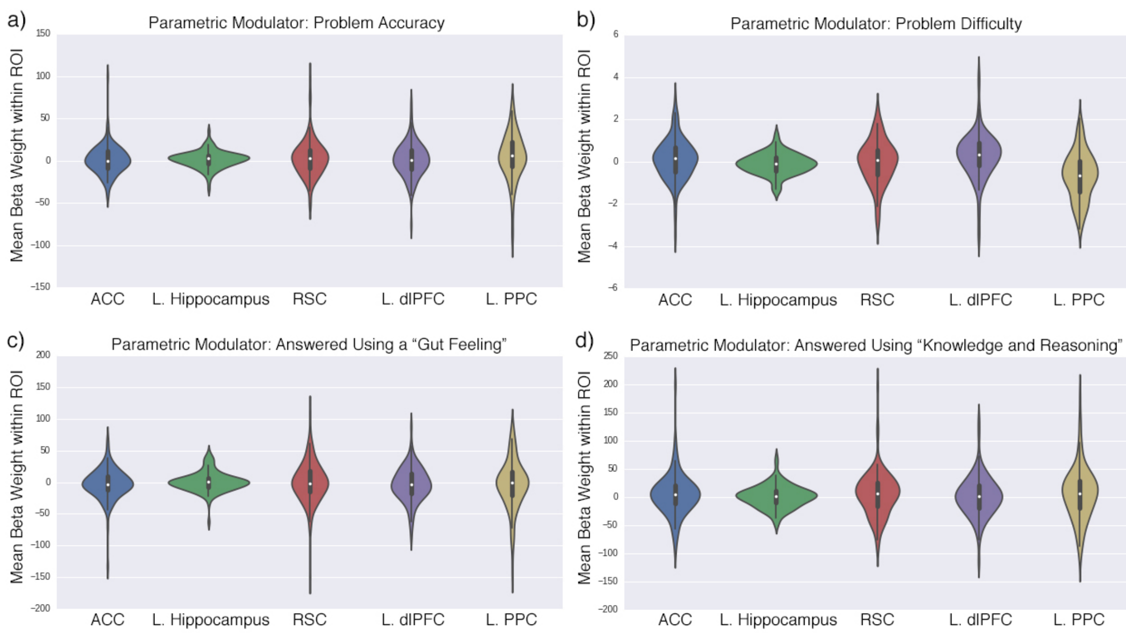


Figure 4.5. Beta Weight Distributions. Mean beta weight distributions for the four parametric modulator analyses within the *a priori* ROIs. a) Problem accuracy, b) difficulty, and c-d) strategy are shown.

4.5.3 Students demonstrate dissociable brain activity linked to knowledge fragmentation

We next performed module analysis (Brewe et al., 2016) on students' answer patterns to probe potential relationships between brain activity and students' conceptual coherence (i.e., integration of physics knowledge; (Redish, 2003)) and to assess if distinct reasoning profiles were rooted in underlying functional brain differences. We analyzed answer distributions using a community detection algorithm (Rosvall and Bergstrom, 2008) to parse student sub-groups who provided similar responses across FCI questions. Percent overlap was assessed between answers provided by each group and previously identified "conceptual modules" present in the FCI test ((Brewe et al., 2016); **Table 4.1**). Conceptual modules are communities of incorrect FCI answer choices that are usually selected together. They represent students' dissociable non-Newtonian (incorrect) notions about physical phenomena, some of which demonstrate a high degree of conceptual coherence, while others are more suggestive of a fragmented collection of physics ideas (Brewe et al., 2016; diSessa, 1993; Scott and Schumayer, 2017). The set of conceptual modules selected by a group (their reasoning profile) represents distinguishable arrangements of student's (mis)interpretations and confusions about the physical world. Module analysis detected thirteen student groups across 107 students who answered similarly to each other during FCI problem solving (**Figure 4.6a)**, and four of these groups had 10 or more members (i.e., normative groups).

Next, we sought to identify any differences that may be present in physics problem solving-related brain function associated with differences in conceptual approach by contrasting the brain activity of the normative groups. All fMRI data had been scrubbed during preprocessing with a common framewise displacement (FD) threshold during preprocessing to eliminate visually identifiable artifacts. However, not all movement artifacts are identifiable via visual inspection of fMRI data, and even small head motions can cause large signal changes that can interfere with the interpretation of fMRI results (Havsteen et al., 2017). So, to avoid any potential motion-related confounds during group comparison of brain function, a one-way ANOVA of mean FD values across the four normative ($n \geq 10$) groups was conducted and a significant difference of in-scanner motion ($F(3, 178) = 8.213$, $p << 0.001$) was detected (mean FD: Group A = 0.072mm, Group B = 0.062mm, Group C = 0.073mm, and Group D = 0.092mm). *Post hoc* tests revealed a single normative group (Group D) showed significantly increased motion relative to all other normative groups ($p < 0.05$; **Figure 4.7**), but no other differences in in-scanner motion existed. Thus, to avoid any potential confounds related to differences in head motion across normative groups, the high motion group was excluded from further analyses. The remaining three groups' answer distributions were characterized based on prevalence of conceptual modules (**Figure 4.6b)**. These groups, composed of 24, 17, and 10 students, were carried into group-level neuroimaging analyses to assess brain activity and connectivity differences during problem solving. Center of mass activation coordinates for the FCI > Control contrast of group differences between the final three normative sub-groups identified by module analysis are shown in

Table 4.7.

Table 4.7. Center of mass coordinates associated, as reported in MNI space, of brain activation (FCI > Control, all Phases) group differences between normative sub-groups

identified by module analysis of student answer distributions. Omnibus test results are listed in (a) and (b), with F-scores converted to z statistics. Results from *post hoc* t-tests investigating differences across each pair of sub-groups are listed in (c)-(h). Cluster region labels are based off those reported by the IBASPM116 Human Brain Atlas.

Cluster	Hemisphere	Center of Mass (MNI space)			Cluster Extent (mm^3)	Mean Z Score	Labels
a) Whole-brain one-way ANOVA: Group A or B vs. Group C							
		X	Y	Z			
1	B	0	-78	6	12384	3.627	Calcarine_L, Lingual_L, Calcarine_R, Cuneus_R, Cuneus_L, Lingual_R, Occipital_Sup_L, Cerebelum_6_L, Precuneus_R
2	L	-48	-18	54	4728	3.504	Postcentral_L, Precentral_L, Parietal_Inf_L
3	L	-8	10	36	1608	3.621	Cingulum_Mid_L, Cingulum_Ant_L, Supp_Motor_Area_L
4	L	-44	50	-4	1592	3.534	Frontal_Mid_Orb_L, Frontal_Mid_L, Frontal_Inf_Orb_L, Frontal_Inf_Tri_L, Frontal_Sup_L
b) Whole-brain one-way ANOVA: Group A or C vs. Group B							
1	B	0	-78	6	12368	3.627	Calcarine_L, Lingual_L, Calcarine_R, Cuneus_R, Cuneus_L, Lingual_R, Occipital_Sup_L, Cerebelum_6_L, Precuneus_R
2	L	-48	-18	54	4720	3.504	Postcentral_L, Precentral_L, Parietal_Inf_L
3	L	-8	10	36	1608	3.620	Cingulum_Mid_L, Cingulum_Ant_L, Supp_Motor_Area_L
4	L	-44	50	-4	1592	3.533	Frontal_Mid_Orb_L, Frontal_Mid_L, Frontal_Inf_Orb_L, Frontal_Inf_Tri_L, Frontal_Sup_L
c) Group A > Group B							
No significant group differences detected							
d) Group B > Group A							
No significant group differences detected							
e) Group A > Group C							
2	L	-44	48	-2	2592	3.409	Frontal_Mid_Orb_L, Frontal_Inf_Tri_L, Frontal_Mid_L, Frontal_Inf_Orb_L
3	R	38	-70	-50	2400	3.356	
4	L	-58	-62	-4	1752	3.418	Temporal_Mid_L, Temporal_Inf_L, Occipital_Inf_L, Occipital_Mid_L
5	R	60	-50	-12	1464	3.409	Temporal_Inf_R, Temporal_Mid_R
f) Group C > Group A							

1	B	-2	-80	6	14232	3.673	Calcarine_L, Lingual_L, Calcarine_R, Cuneus_R, Cuneus_L, Lingual_R, Occipital_Inf_L, Occipital_Mid_L, Fusiform_L, Cerebelum_6_L, Cerebelum_Crus1_L, Occipital_Sup_L
2	L	-46	-18	54	9496	3.643	Postcentral_L, Precentral_L, Parietal_Inf_
3	B	0	10	42	6640	3.522	Supp_Motor_Area_R, Cingulum_Mid_L, Cingulum_Mid_R, Supp_Motor_Area_L, Cingulum_Ant_L, Cingulum_Ant_R, Frontal_Sup_R
4	R	46	-12	52	3648	3.464	Precentral_R, Frontal_Mid_R, Postcentral_R
5	R	46	12	-10	2688	3.640	Insula_R, Temporal_Pole_Sup_R, Frontal_Inf_Orb_R
6	L	-48	8	-8	1840	3.410	Temporal_Pole_Sup_L, Insula_L, Temporal_Mid_L, Temporal_Sup_L, Rolandic_Oper_L
7	L	-56	-24	8	1680	3.414	Temporal_Sup_L, Temporal_Mid_L, Postcentral_L, Heschl_L, Rolandic_Oper_L
g) Group B > Group C							
1	L	-48	48	-6	1328	3.465	Frontal_Mid_Orb_L, Frontal_Inf_Orb_L, Frontal_Inf_Tri_L, Frontal_Mid_L
h) Group C > Group B							
1	B	2	-72	8	10664	3.448	Lingual_L, Lingual_R, Calcarine_L, Cuneus_R, Calcarine_R, Precuneus_R, Vermis_6, Cuneus_L, Cerebelum_4_5_L, Vermis_4_5, Cerebelum_6_L, Cerebelum_6_R
2	L	-20	-50	-8	256	3.243	Lingual_L, Fusiform_L
3	R	26	-74	6	40	3.175	No label generated

Group A (n=24) achieved an accuracy rate of 77% across all FCI questions, indicative of being highly Newtonian thinkers (Savinainen and Scott, 2002). Of the non-Newtonian responses provided by this group, incorrect answers almost exclusively aligned with a common naïve physics idea known as the '*impetus force*' (*m1*, **Figure 4.6b** top), which is the incorrect belief that moving objects experience a propelling force. Group B (n=17) achieved an accuracy rate of 73% across all FCI questions, which is also indicative of high Newtonian thinking. The reasoning profile for Group B (**Figure 4.6b** middle) indicated that students gave incorrect answers by either falling victim to the *impetus force fallacy* (*m1*) or to another common, but less coherent set of physics conceptions that we term the '*confusion about gravitational action' module* (*m9*). Group C (n=10) achieved an accuracy rate of 53% across all FCI questions, indicative of non-Newtonian thinking. The reasoning profile for Group C (**Figure 4.6b** bottom) indicated that students' incorrect answers were primarily associated with 5 conceptual modules that each occurred at relatively similar rates: the '*impetus force' module* (*m1*), '*more force yields more result' module* (*m2*), '*confusion relating speed and path' module* (*m5*), '*sudden forces induce instantaneous path change' module* (*m6*), and 'an *object's mass determines how it falls' module* (*m7*).

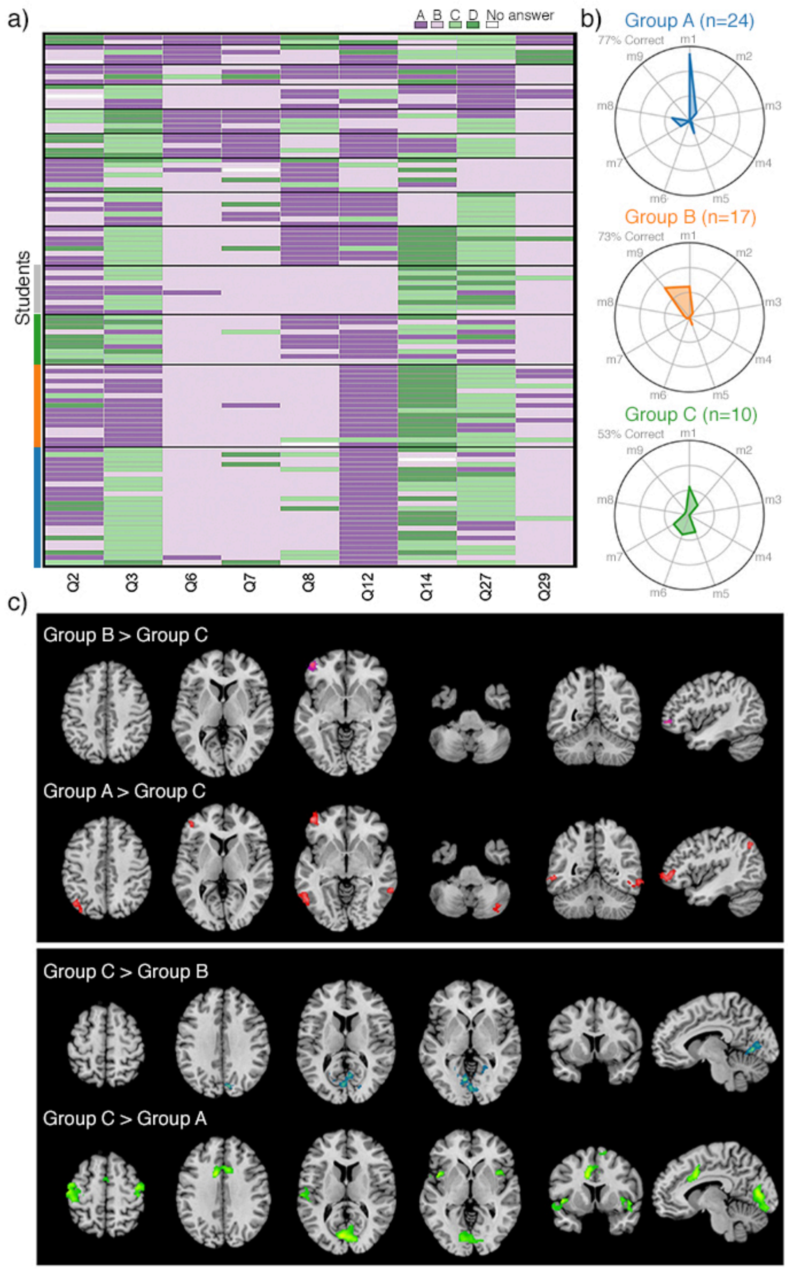


Figure 4.6. Module Analysis, Reasoning Profiles, and Group Differences in Brain Activity. a) Module analysis of student responses across FCI answer distributions. Heat map colors represent student responses to multiple-choice FCI questions and black horizontal lines distinguish groups identified by community detection. b) Scaled within-group overlap of incorrect FCI responses across a nine previously measured physics conceptual models ((Brewe et al., 2016); **Table 4.1**) for top three normative groups. c) Group differences in problem solving-related brain networks (FCI > Control, all phases) across the three normative groups. Increased activity is shown for Groups A and B relative to Group C (top) and Group C relative to Groups A and B (bottom). No significant differences were observed between Groups A and B.

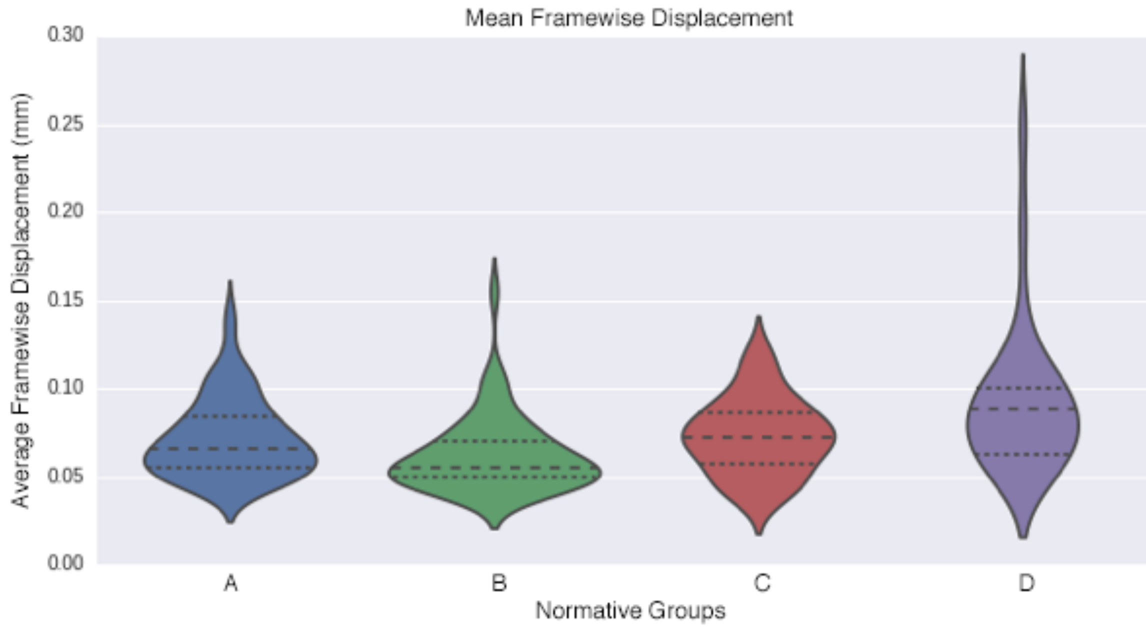


Figure 4.7. Mean Framewise Displacement Distributions for Normative Groups. Mean framewise displacement (FD; mm) for the four normative ($n \geq 10$) sub-groups identified by module analysis of FCI answer distributions. ANOVA indicated a significant difference in mean FD head motion between groups one or more of the groups ($p << 0.001$). Post-hoc multiple comparison Turkey HSD tests indicated students in Group D showed to significantly greater head motion ($p < 0.05$) relative to groups A-C, thus Group D was excluded from further analysis.

We performed a whole-brain, one-way ANOVA to identify between-group differences in physics-related brain activity (FCI > Control, all phases). Omnibus results indicated that one or more sub-groups showed significantly different brain activity during problem solving. *Post hoc* tests were performed across each combination of group pairs (**Figure 4.6c**;

Table 4.7). Group A (vs. C) students demonstrated greater activity during problem solving in the left lateral orbitofrontal cortex (lOFC) as well as in the left inferior parietal lobule, bilateral V5/MT+, and right cerebellum. Group B (vs. C) students also exhibited greater activity in the left lOFC. Group C (vs. both A and B) students showed greater activity in the cuneus extending into the lingual gyri. Additionally, Group C students also showed increased activity relative to Group A in the caudal medial frontal gyrus, ACC, bilateral precentral and postcentral gyri along the precentral sulcus, bilateral anterior insular cortex (aIC), and left superior temporal gyrus. Overall, student who answered using more coherent physics conceptions, even if incorrect, showed increased reliance on a lOFC-V5/MT+ network, whereas students who held less consistent ideas involving multiple conceptual approaches showed increased primary visual and salience activity, suggesting the absence of stable and coordinated physics conceptions may force students to rely more heavily on scenario visualization and stimuli detection during problem solving. Further work investigating these differences could yield valuable instructional implications.

4.5.4 Response Times

Average response times (RT) for FCI and control questions across all students were 20.2s and 15.7s respectively (FCI Phase I: 6.4s, Control Phase I: 6.8s; FCI Phase II: 5.1s, Control Phase II: 2.8s; FCI Phase III: 8.6s, Control Phase III: 6.1s; **Figure 4.8**). Reasoning sub-group FCI and control RTs (across all phases) were 21.2s and 15.7s for Group A, 18.1s and 14.4s for Group B, and 20.1s and 16.8s for Group C (**Figure 4.9**). We conducted statistical comparisons to determine if differences in RT were present across problem phases, conditions, and reasoning sub-groups.

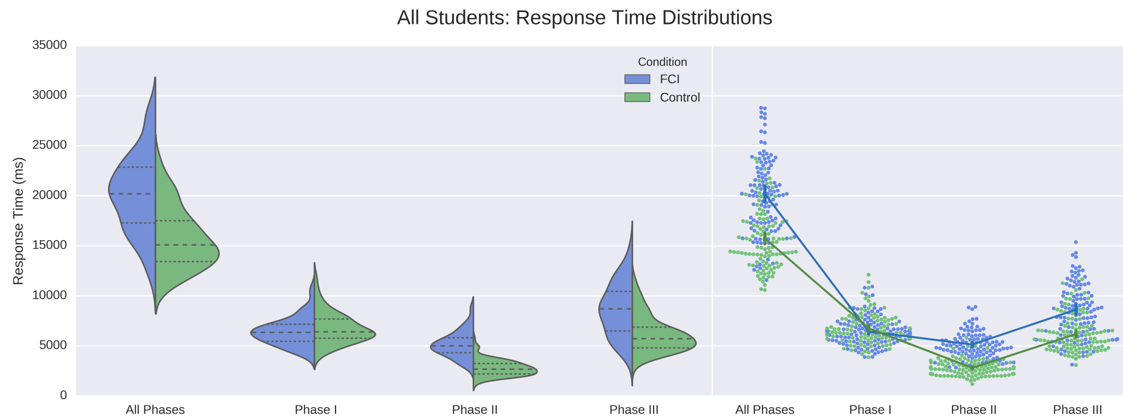


Figure 4.8. Mean Response Times Across FCI Phases. Mean response times (RT; ms) across all students for the FCI and Control condition (all phases) as well as each sequential phase. Kernel density estimates of RT distributions are plotted on the left and the interaction across conditions is provided on the right, with 95% confidence intervals shown as vertical error bars. Students spent significantly more time answering FCI questions compared to Control questions, except within Phase I, and significantly more time in both conditions in Phase III, Phase I, and Phase II, respectively (p << 0.001).

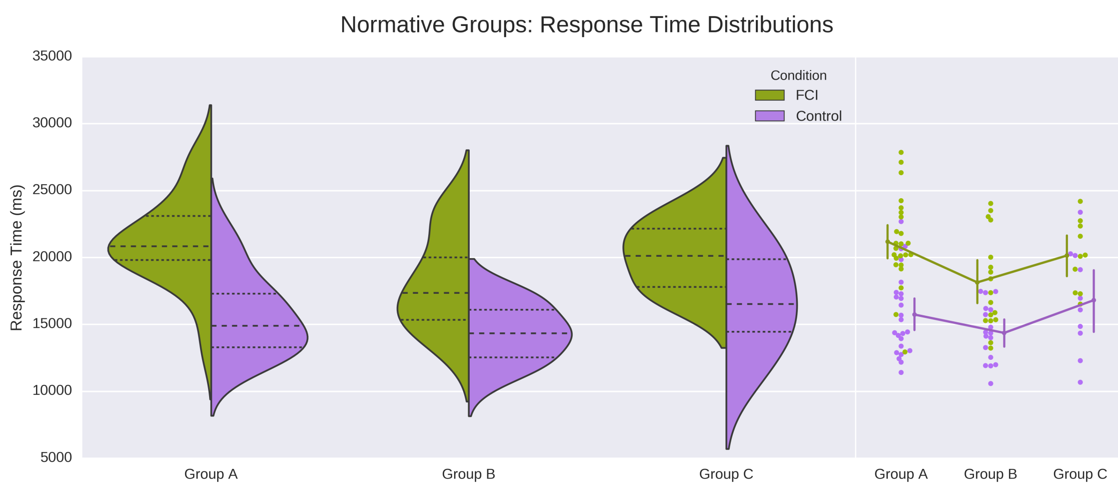


Figure 4.9. Mean Response Times Across Normative Groups. Mean response times (RT; ms) for normative sub-groups across all Phases for FCI and Control conditions. Kernel density estimates of RT distributions are plotted on the left, and the interaction across conditions and groups is provided on the right, with 95% confidence intervals shown as vertical error bars. Significant differences were observed between FCI and Control RTs across all sub-groups (p << 0.001). Turkey HSD *post hoc* tests indicated no significant pairwise RT differences in either condition between sub-groups.

In a comparison across all 107 student responses, significant RT differences were detected between FCI and Control conditions across full question blocks (all phases; $p \ll 0.001$). A two-way mixed effects ANOVA: condition (FCI, Control) x Phase (Phase I, Phase II, Phase III) was also conducted to compare the main effects of phase and condition and the interaction between phase and condition on RT. A significant two-way interaction between phase and condition was detected ($F(2,535) = 62.860$, $p \ll 0.001$), indicating RTs differed across conditions and phases. Turkey HSD *post hoc* tests were conducted on the family of six estimates and all but two pairwise comparisons were significant (see

Table 4.8 for a summary these multiple comparisons.) No significant RT differences were detected between conditions at Phase I, or between Phase III FCI RT and Phase I Control RT. All other comparisons were significant at $p < 0.001$ except for the Phase I, Control RT - Phase III, Control RT contrast, which was significant at $p < 0.05$. These results indicate students spent significantly more time answering FCI questions as compared to Control questions, except within Phase I. Students also spent significantly more time in Phases III, I, and II, respectively across both conditions.

Additionally, to investigate potential RT differences across normative reasoning groups, we conducted one-way ANOVAs testing within-condition mean RT across reasoning sub-groups. A significant difference in RT across sub-groups was detected for the FCI condition ($F(2,48) = 4.315$, $p < 0.05$) but not for the Control condition RTs ($F(2,48) = 2.269$, $p = .114$). However, turkey HSD *post hoc* tests revealed no significant pairwise FCI RT differences between normative groups after correcting for multiple comparisons. A two-way mixed effects ANOVA: condition (FCI, Control) x Group (Group A, Group B, Group C) was also conducted to compare the main effects of group and condition and the interaction between group and condition on RT. The effect of group was significant, yielding an F ratio of $F(2,48) = 3.8139$, $p < 0.05$. However, as before, *post hoc* multiple comparison Turkey HSD tests indicated no significant pairwise differences between groups ($p < 0.05$, adjusted for multiple comparison using the Holm method.) The effect of condition yielded an F ratio of $F(1,48) = 100.5341$, $p << 0.001$, indicating a significant difference in RT between FCI and Control conditions. The interaction effect between condition and group was not significant, $F(2,48) = 2.1661$, $p = 0.1257$.

RT differences between conditions, phases, and groups were influenced by students' ability to choose when they felt ready to progress to the next phase and when they had finished answering each question. This self-paced task structure emulated that of real-world problem-solving processes and ensured measured brain activity associated with each phase corresponded to intervals in which students were initiating problem solving (Phase I), reading and comprehending the question (Phase II), and choosing an answer (Phase III). While it is possible that RT differences may have impacted the brain activation results we were able to detect, we nonetheless believe allowing for students' authentic and variable problem solving approach was of critical importance in measuring students' problem solving processes. We hold that these RT differences are a central to part of the problem-solving processes.

Table 4.8. Two-way mixed effects ANOVA of condition on response time (RT). A significant interaction was detected in the two-way mixed effects ANOVA of Condition of (FCI, Control) x Phase (Phase I, Phase II, Phase III) on RT across all 107 students. Results from follow up Turkey HSD *post hoc* tests on the family of six estimates are provided below.

Contrast	Estimate	SE	df	t ratio	P value
Phase I Control - Phase II Control	3966.642	198.0183	535	20.032	<.0001
Phase I Control - Phase III Control	592.2531	198.0183	535	2.991	0.0344
Phase I Control - Phase I FCI	329.6553	198.0183	535	1.665	0.5558
Phase I Control - Phase II FCI	1633.9599	198.0183	535	8.252	<.0001
Phase I Control - Phase III FCI	-1850.9198	198.0183	535	-9.347	<.0001
Phase II Control - Phase III Control	-3374.3889	198.0183	535	-17.041	<.0001
Phase II Control - Phase I FCI	-3636.9866	198.0183	535	-18.367	<.0001
Phase II Control - Phase II FCI	-2332.6821	198.0183	535	-11.78	<.0001
Phase II Control - Phase III FCI	-5817.5617	198.0183	535	-29.379	<.0001
Phase III Control - Phase I FCI	-262.5977	198.0183	535	-1.326	0.7704
Phase III Control - Phase II FCI	1041.7068	198.0183	535	5.261	<.0001
Phase III Control - Phase III FCI	-2443.1728	198.0183	535	-12.338	<.0001
Phase I FCI - Phase II FCI	1304.3045	198.0183	535	6.587	<.0001
Phase I FCI - Phase III FCI	-2180.5751	198.0183	535	-11.012	<.0001
Phase II FCI - Phase III FCI	-3484.8796	198.0183	535	-17.599	<.0001

4.6 Discussion

In this study, we investigated the neural mechanisms underlying physics reasoning across 107 students and identified a fronto-temporo-parietal brain network linked with problem solving. Initiation, question presentation, and answer selection phases evoked integrated V5/MT+, CEN, DAN, and DMN systems. Notably, during answer selection wherein students deliberated between possible outcomes linked to conflicting physics conceptions, they engaged concurrent V5/MT+, lateral fronto-parietal, and DMN activity, evidencing V5 -CEN-DMN engagement as critical for physics reasoning. Follow-up PPI analyses investigating task-based FC between V5/MT+, dlPFC, and RSC found evidence that physics reasoning initiates dorsal stream activity and CEN-DMN information exchange. Strategy and accuracy did not modulate brain activity during reasoning; however, increased difficulty elicited enhanced DAN engagement, representative of reliance on executive functions during demanding problems. Importantly, whole brain activity was not modulated by problem-solving accuracy, but module analysis resulting in a dissociation of student reasoning sub-groups (i.e., problem solvers grouped by similar conceptualizations of physics ideas) yielded ranked performance differences across groups that were linked to conceptual approach. Compellingly, students from groups who applied more Newtonian and coherent physics conceptions showed enhanced engagement of a fronto-temporal network, whereas students who relied on less coherent, non-Newtonian conceptions engaged enhanced visual and SN area activity during problem solving. These insights aid in characterizing the underlying neural processes of how students tackle conflicting physics conceptions during reasoning.

4.6.1 Visualization, association, and mental exploration inform physics problem solving.

When students solve physics problems they activate a network of bilateral dlPFC, left lOFC, PPC, RSC, and V5/MT+ areas, consistent with previous CEN-supported problem-solving findings across knowledge domains (Bartley et al., 2018). Yet, V5/MT+ and RSC involvement with the CEN appear to be a feature of physics problem solving in particular. Both areas support visuospatial information processing (Kravitz et al., 2011), with V5/MT+ linked to imagining implied motion and maintaining motion information in working memory (Galashan et al., 2014; Kourtzi and Kanwisher, 2000; Senior et al., 2000), and RSC supporting spatial cognition and episodic memory retrieval, especially when imagined scenes are mentally transformed between specific viewpoints (Vann et al., 2009). Thus, these regions may aid in the mental imagery of motion, as informed by remembered physical scenarios, and build internal representations of physical systems, which is considered an essential step in physics solution generation (National Research Council, 2012a). Shifts in physics-related brain activity across problem phases indicate reliance on memory-linked associations. We find V5/MT+, CEN, DAN, and DMN transitions support sequential problem-solving phases. Notably, answer generation elicited concurrent DMN, lateral fronto-parietal, and V5/MT+ activity. Interestingly, while CEN-supported tasks often evoke DMN deactivations, this DMN-CEN coherence likely indicates reliance on episodic and semantic memory retrieval processes (Andrews-Hanna et al., 2014; Binder et al., 2009) during physics cognition, a notion consistent with the constructivist theory of learning (Fosnot and Perry, 2013). Additionally, the PCC is functionally heterogeneous, connecting DMN and fronto-parietal networks, and serving as a possible hub across brain systems to direct attentional focus (Leech and Sharp, 2014). Further, the FCI is differentiated from other fMRI tasks by its relatively long trials, requiring sustained cognition to generate answers. The DMN may thus be activated along with the CEN to allow for mental exploration necessary in solution derivation.

4.6.2 Problem solving-related brain activity differs based on how students think, not how correct they are.

We find students' problem solving-related brain function cannot be categorized by simply considering their "*incorrect*" vs. "*correct*" answers. Rather, module analysis indicates variance in conceptual approach better characterizes brain differences, which in turn impacts success rate. An existing framework of learning conceptualizes physics cognition as relying on dual "knowledge structure" and "control structure" processes (Redish, 2003). Under this model, students apply executive functions to select or inhibit associational patterns that ground how they describe the physical world. Here, associational patterns, known as knowledge structures, are conceptualized as flexible, contextually-primed collections of linked knowledge elements called "resources" that students activate to scaffold reasoning. Ideally, students learn to activate stable associations between physical laws, enabling long deductive chains to be carried out during problem solving. However, when this does not occur, student's non-Newtonian processes can vary: strongly associated yet inappropriate resources may stably activate across contexts, or more basic, axiomatic physical beliefs (e.g., intuitive notions such as *closer is stronger* or *more effort gives more result*; (diSessa, 1993)) may form weak, unstable links that do not support ancillary deductive elaboration. These differences are described along an axis of "compilation" or memory chunking. Students without pre-compiled knowledge structures require additional cognitive resources to assemble associations during reasoning, whereas physics experts can access well-developed associational patterns that do not need to be actively assembled during problem solving.

We adopt this resources framework to interpret brain function with the goal of relating neuroimaging findings to classroom instruction. Physics-related CEN and DAN activations were linked to varied cognitive terms consistent with the idea of a control structure, and DMN involvement during reasoning may reflect associational mappings within semantic or episodic memory circuits (Andrews-Hanna et al., 2014; Binder et al., 2009). Thus, dlPFC-RSC FC may support the idea that control processes guide knowledge structure selection. Under this interpretation, reasoning sub-groups may be thought of as differentiated by knowledge structure use. Groups A and B applied predominantly Newtonian (i.e., compiled) thinking, but Group C was less consistent in their approach. Of the non-Newtonian modules activated, Group A consistently used an arguably concrete *impetus* model, Group B applied an *impetus* model while also expressing *confusion about gravitational action*, and Group C utilized multiple modules characterized by simple, vague, or confused ideas that differed across problems. We argue these groups can be described along a continuum of knowledge compilation, coherence, and robustness. Groups A and, to a lesser extent, B demonstrated stable, strongly associated knowledge structures, whereas Group C showed more labile associational patterns that were limited by problem context. In this manner, less coherent, more variable knowledge structures were associated with increased primary visual and SN activity, whereas pre-compiled, stable reasoning strategies more strongly activated lOFC and V5/MT+, areas implicated by physics thinking in the CEN. These findings suggest that chunked knowledge can reduce working memory demands, allowing for increased focus on other control structure aspects of problem solving (Redish, 2003). However, when students continually re-identify associational patterns across problems, they may rely more heavily on visually guided SN activity to select which problem features deserve their attention (Sarathy, 2018).

4.6.3 Relating neuroeducational findings to the classroom.

A fundamental goal of neuroeducation research is to bridge understanding of brain function with meaningful classroom practices. Under a resources framework, our results suggest physics students struggle most when they do not understand how to choose appropriate and coherently chunked resources from long-term memory, thus relying on increased SN activity during problem solving. Learning obstacles also occur when students access compiled but non-physical conceptions during reasoning, allowing for increased CEN brain function linked to control processes. While the latter still represents a type of incorrect physics thinking, it more closely resembles the kind of cognition instructors aim to teach (Redish, 2003). These insights can inform classroom practice: physics instruction that explicitly attends to how students select, link, and reorganize resources is essential in developing appropriately compiled knowledge to map back onto control processes (Redish, 2003). Learning physics is complex, yet a disproportionate focus is often placed on whether students answer questions correctly. Our results indicate the conceptual foundations of wrong answers reveal much more about student's ability to succeed, can explain functional brain differences during reasoning, and may guide instruction. A focus on accuracy alone over-simplifies the complex processes engaged during physics reasoning. Instructors should facilitate conceptual change that emphasizes and leverages students' existing conceptions to transition resources into stable and accessible collections that help connect what students believe with what they predict.

In sum, we find the neural mechanisms underlying conceptual physics problem solving are characterized by integrated visual motion, central executive, attentional, and default mode brain systems, with solution generation relying on critical DMN-CEN engagement during reasoning. Furthermore, we explored whether measures of student success show underlying neurobiological bases, finding that students' physics conceptions manifest as brain differences along an axis of relative knowledge fragmentation and robustness. Critically, accuracy alone did not predict brain function, but students achieved increased success when they made use of stable, strongly associated knowledge structures. We acknowledge that our results may be specific to the FCI questions used here, and that additional or varied brain dynamics may be more relevant for different kinds of physics problem solving. Despite this concern, we are confident that our findings serve to deepen understanding into how students learn. Together, our results demonstrate associational and control processes operate in tandem to support physics problem solving and offer insight into effective classroom practices to promote student success.

Chapter 5

Toward a neurobiological basis for understanding learning in University Modeling Instruction physics courses

5.1 Abstract

Modeling Instruction (MI) for University Physics is a curricular and pedagogical approach to active learning in introductory physics. A basic tenet of science is that it is a model-driven endeavor that involves building models, then validating, deploying, and ultimately revising them in an iterative fashion. MI was developed to provide students a facsimile in the university classroom of this foundational scientific practice. As a curriculum, MI employs conceptual scientific models as the basis for the course content, and thus learning in a MI classroom involves students appropriating scientific models for their own use. Over the last ten years, substantial evidence has accumulated supporting MI's efficacy, including gains in conceptual understanding, odds of success, attitudes toward learning, self-efficacy, and social networks centered around physics learning. However, we still do not fully understand the mechanisms of how students learn physics and develop mental models of physical phenomena. Herein, we explore the hypothesis that the MI curriculum and pedagogy promotes student engagement via conceptual model building. This emphasis on conceptual model building, in turn, leads to improved knowledge organization and problem solving abilities that manifest as quantifiable functional brain changes that can be assessed with functional magnetic resonance

imaging (fMRI). We conducted a neuroeducation study wherein students completed a physics reasoning task while undergoing fMRI scanning before (pre) and after (post) completing a MI introductory physics course. Preliminary results indicated that performance of the physics reasoning task was linked with increased brain activity notably in lateral prefrontal and parietal cortices that previously have been associated with attention, working memory, and problem solving, and are collectively referred to as the central executive network. Critically, assessment of changes in brain activity during the physics reasoning task from pre- versus post-instruction identified increased activity after the course notably in the posterior cingulate cortex (a brain region previously linked with episodic memory and self-referential thought) and in the frontal poles (regions linked with learning). These preliminary outcomes highlight brain regions linked with physics reasoning and, critically, suggest that brain activity during physics reasoning is modifiable by thoughtfully designed curriculum and pedagogy.

5.2 Introduction

Active learning is neither a curriculum nor a pedagogy. Active learning is a class of pedagogies and curriculum materials that strive to more fully engage students and promote critical thinking about course material. Students learn more effectively when they engage in investigations, discussions, model building, problem solving, and other active explorations (National Research Council, 2012b; *Reaching Students: What Research Says about Effective Instruction in Undergraduate Science and Engineering*, 2014). However, typical university instruction in physics (and other Science, Technology, Engineering, and Mathematics [STEM] fields) has been lecture-based. While lectures can be interesting, and some students clearly have been trained to become engaged during lectures (Schwartz and Bransford, 1998), for the majority of students, lectures are passive activities. This mismatch between the ways that students learn and the way many classes are taught is the primary motivation for the transformation of STEM instruction. When classrooms are transformed, the evidence is overwhelming; students learn more and are more likely to succeed in active learning settings (Scott Freeman et al., 2014).

Multiple transformative curricula and pedagogical approaches have been developed for introductory physics to promote active learning. For example, *Peer Instruction* emerged to enhance standard lecture-based approaches by incorporating conceptual questions for discussion and, in turn, facilitated development of personal response systems (Crouch and Mazur, 2001). *Tutorials in Physics* were developed to supplement standard lectures through use in recitation sections (McDermott et al., 2001). Other materials such as *Student Centered Active Learning Environment with Upside-down Pedagogies* [SCALE-UP] (Beichner and Saul, 2003) and *Investigative Science Learning Environments* [ISLE] (Etkina, Murthy, & Zou, 2006; Etkina & Van Heuvelen, 2007) implement a studio-format that integrates lab and lecture, including greater amounts of conceptual reasoning and greater emphasis on exploration. Modeling Instruction (MI) is an active learning approach (Brewe, 2008) similar to SCALE-UP and ISLE in that it is a complete course transformation integrating lab and lecture components into one studio format class. However, MI is distinct from other reforms in that it was built around an explicit epistemological theory of science, and this foundation is one of the motivations for using functional magnetic resonance imaging (fMRI) to study how learning physics may impact brain network development.

Hestenes (1987) avers that science by its very nature is a modeling endeavor. Science proceeds by developing models that describe and ultimately predict phenomena. As a model is developed, it is validated through the interplay between the predictions generated by the model and the evidence that emerges supporting such predictions. Once a valid model has been developed, the model is deployed to new situations. This is a process which Kuhn (1970) called "normal science", whereby scientists use existing prevalent models to explore the models' limits of applicability and search for places where the models give rise to predictions in contrast with evidence. Ultimately, models reach their limits of applicability and need to be revised or in some cases abandoned entirely, beginning what Kuhn called "revolutionary science." When this happens, a new model is proposed, and the cycle begins anew.

The modeling theory of science is the theoretical and epistemological basis of MI. This, however, is a theory of *science*, not a theory of *science instruction*. It translates to instruction through the premise that, if modeling is how science proceeds and we believe students should be engaged in authentic scientific practices, then instruction should be designed to engage students in the process of modeling. Wells, Hestenes, and Swackhamer, (1995) describe the Modeling Cycle as the recursive process of engaging students in model development, validation, deployment, and revision.

In this paper, we first provide an overview of the theoretical background, development process and critical features behind MI as a transformative curricula and model-building endeavor. This overview serves to motivate why scientific model development in students resulting from university instruction warrants further investigation not only at the academic (e.g., grades) and social level (e.g., social networks) but also at the neurobiological level as a putatively measurable phenomena that occurs within the brain. Then, we shift focus to present results from a fMRI study in which we measured brain activity among students engaged in physics reasoning and model use before and after they completed a MI course. We subsequently discuss the results which show distinctive brain activity related to physics reasoning and that instruction consistent with a Modeling theory of science modifies brain activity from pre to post course.

5.2.1 Role of Conceptual Models in Introductory Physics Curriculum

Building instruction around modeling necessitates a working understanding of models. To date, research in the MI context has focused on conceptual models, which are instructionally useful, rather than mental models, which have been difficult to directly observe. Herein, we seek to expand upon existing research by adopting neuroimaging techniques to interrogate mental models among students receiving instruction via an explicit conceptual modeling approach (i.e., MI). We operate from the following definition of a conceptual model: conceptual models are purposeful coordinated sets of representations (e.g., graphs, equations, diagrams, or written descriptions) of a particular class of phenomena that exist in the shared social domain of discourse. This definition has several features worth elaborating. First, it fits on a t-shirt. Second, this definition establishes the domain, purpose, and composition of conceptual models, which we expand upon below. Finally, this definition of conceptual models has helped us design research to look for evidence of the modeling process in classrooms. **Figure 5.1** illustrates the relationship between conceptual and mental models.

Attempting to synthesize the many definitions and descriptions of models is not our purpose. Instead, we aim to highlight some of the features of our definition that were relevant to the development of the MI approach based on building, validating, deploying and revising models. These features (i.e., the composition, purpose, and domain of conceptual models), then will be used to structure the investigations into the nature of student's mental model formation as measured via brain-based fMRI data.

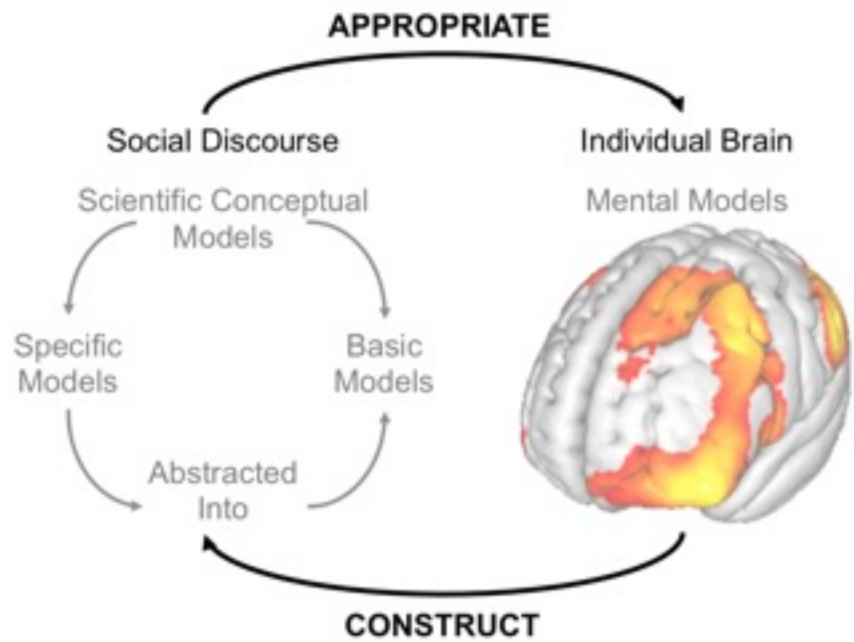


Figure 5.1. Conceptual and Mental Models Schematic. Schematic of the relationship between conceptual and mental models in physics curriculum.

5.2.1.1 Composition

Conceptual models are composed of representations. Representations are human inventions/constructs that stand in for the phenomena (Giere, 2005; Morgan and Morrison, 1999; Schwarz et al., 2009; Center for the Study of Language and Information

(U.S.), 2006; Windschitl and al, 2008). In physics, common types of representations include graphs, vector diagrams, equations, simulations, words, and pictures (Krieger, 1987). From the MI perspective, this means that instruction should focus on helping students to identify, use, and interpret representational tools that are useful in describing physical systems. Instruction around model building necessarily focuses on what representations are common to a discipline, how they are used, and how information can be extracted from them. Further, the coordination of these representations helps to build a more robust model, and provide a variety of ways to extract information from the model (Halloun, 2004; Hestenes, 1992).

5.2.1.2 Purpose

Morgan & Morrison (1999) described mental models as mediators of thought, autonomous from, but in correspondence with the system they represent. This mediating function of models establishes the roles that models have within science as the center of thought, explanation, and prediction (Craik, 1943; Johnson-Laird, 1983). For example, Craik (1943) stated, "*If the organism carries a 'small-scale model' of external reality and of its own possible actions within its head, it is able to try out various alternatives…*" Instructionally, if models fill this role of mediators of thought, then models should structure the organization of the curriculum. Models also allow students to address new phenomena (Gouvea and Passmore, 2017; Odenbaugh, 2005; Svoboda and Passmore, 2013). This purpose is built into the instructional modeling cycle where students are encouraged to understand new phenomena by deploying existing models to extract information about and characterize the phenomena. When existing models do not work, students are expected to adapt or redevelop models that can account for these new phenomena.

5.2.1.3 Domain

We propose a distinction between *scientific conceptual* and *mental model domains* and place conceptual models in the shared social domain of discourse. This perspective differs from other conceptualizations where mental models within individuals' minds/brains are implicitly or explicitly the center of focus (Greca & Moreira, 2001; Greca & Moreira, 2000). Specifically, to infer the status of a student's mental model, investigators typically assess students' actions or behaviors, such as writing, speaking, drawing, predicting, or arguing (I. Halloun, 1996; Justi and Gilbert, 2000; Lehrer and Schauble, 2006). Thus, evidence of model-based reasoning exists external to the individual and is contingent on an external evaluation. Instructionally, our efforts have been to help students develop models as a distributed cognitive element. Meaning that each individual student will have an instantiation of the shared model, but the visible elements of the model exist external to individuals through writing, speaking, drawing, diagraming, predicting, and/or simulating. This notion of shared models improves team performance and the learning process (Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers 2000). As such, the design of the MI curriculum and pedagogy focuses not on mental models per se, but on the social construction of a model. In other words, we focus students on using consistent representational tools to build models of phenomena in an interactive team environment. Models are shared among class members and agreed upon before deploying these models to analyze new situations. We provide a more detailed description of the classroom setting in Section 1.3 but much of class time is spent in small groups developing models of specific phenomena on small portable whiteboards, which are then presented at larger "board meetings." The interplay between smaller and larger groups provides a vehicle for students to use diagrams, equations, or graphs to represent elements of the model.

We do not reject that individuals have internal mental models, or that these mental models include connections between representations and concepts, or interactions between mathematics and intuition, for example. As Rogoff (1990) points out, cognitive functions are essential components of purposeful action. We are aligned with the notion that scientific conceptual models are distributed cognitive elements, which are then appropriated by individuals. During the appropriation, students construct the mental models in correspondence with the scientific conceptual models. Rather our point is that assessing external behaviors speaks to the conceptual model domain and assessing the mental model domain would benefit from directly considering the brain.

5.2.2 Role of Conceptual Models in Instruction

For instructional purposes, models represent an appropriate and accessible level of abstraction (Halloun, 2004). Within a larger context, models occupy the middle level of a conceptual hierarchy (**Table 1**; Halloun, 2004; Matthews, 2007) which is best illustrated by a representative example (Lakoff, 1987). Veterinarians are not likely to study the superordinate category of animals, which is too broad a categorization to be useful. Nor are they likely to study the subordinate category of retrievers; this is too specific to be broadly useful. Instead, dogs are likely to be the level of focus. This level is referred to as the "basic" level and is considered the ideal focus for instruction (Halloun, 2004).

Table 5.1. Conceptual and Categorical Hierarchies

Hierarchy	
Conceptual	**Categorical**
Theory	Animal
Model	Dog
Concept	Retriever

In the MI classroom, building basic conceptual models begins with considering a specific phenomenon to be described. Once a target phenomenon is established, the next step is to characterize the phenomena through relevant representational tools. For example, using velocity versus time graphs to represent the motion of a moving object. As students create representations of the object's motion, a model of this specific phenomenon is being developed, or what we call a *specific model*. These specific models are not generally applicable, they pertain to the specific details of the situation being considered. By necessity, specific models are predecessors to *basic models*. Specific models are made more robust as additional representational tools are introduced and integrated with existing ones. Introduction of representational tools and the subsequent negotiation of their use and interpretation are motivated by specific phenomena to be modeled, so the models created are always specific models.

However, a desirable scientific skill is to reason based on *general models* (Nersessian, 1995, 2002a, 2002b). As such, the MI curriculum and pedagogy is specifically designed to facilitate the students' transition from specific to basic models. Basic models, which are general and represent entire classes of phenomena (such as a constant acceleration model), are abstracted from a collection of specific models (Halloun, 2004; I. A. Halloun, 1996). For example, the general features of a basic constant acceleration model can be abstracted from specific models of objects undergoing constant acceleration, such as objects in free fall, or uniformly slowing down. This is achieved in the MI classroom by having students consider a number of specific models, and then identifying the features that are similar to all such models. For example, all constant acceleration models include a linear velocity time graph. These similar features are then compiled into one model that can be used for all situations, a basic model. Basic models are useful because they are not tied to a specific phenomenon, much like the Standard Model is a basic model built up and abstracted from the specific models of atomic collisions, particle interactions, etc. Basic models are essential in science as they promote abstract reasoning about novel phenomena (Nersessian, 1995); when physicists seek to understand interactions of atomic particles they start by using the Standard Model.

Once a basic model is established, students deploy the model in a variety of settings. This deployment phase is most aligned with the standard problem solving that happens in physics classes. The purpose is to develop skill at adapting the representations that make up the model to new situations and extracting information about the situation from the representations.

The final stage in the MI instructional cycle is revision. Revision of a basic model happens when students encounter a phenomenon that does not fit with the model's assumptions. An example often encountered comes when students attempt to generate a specific model of two-dimensional motion on the basis of a one-dimensional constant acceleration model. The one-dimensional case is inadequate without modification to understand motion in two dimensions, and thus must be revised. In some cases, revision involves a simple modification of the representational tools, and in other cases, it requires starting with an entirely different model.

In summary, the modeling cycle of MI describes the progression of course content. In addition, MI also interweaves social interactions designed to facilitate discourse in the service of building conceptual models. Next, we more fully describe the precise aspects of the MI learning environment that support the development, validation, deployment, and revision of models.

5.2.3 Features of MI Learning Environment

Basic conceptual models are often well-developed for scientists and course instructors, yet these models are not well-developed for the students in introductory physics courses. Accordingly, the first contextual feature of the MI classroom is to support students in re-developing constituent basic models within their own learning environment. The MI instructor's role is thus to guide students through the development of these basic conceptual models by establishing activities and providing scaffolding to manage student discourse and promote model building and deployment. In this way, the MI curriculum and pedagogy can be considered a guided inquiry approach. Students are not expected to discover physical laws without strong instructor guidance who chooses activities, introduces representational tools, and guides students toward their appropriate use and interpretation. In this way, the instructor is a guide to the disciplinary norms and tools.

5.2.3.1 Student participation in a model-centered learning environment

Accomplishing this fundamental re-development of basic conceptual models requires students to be active and engaged participants in the learning environment. Accordingly, there are specific ways MI students are expected to participate in the re-development of basic conceptual models. First, students are expected to be involved in identifying the way that tools such as pictures, diagrams, graphs, and equations are used to represent phenomena. They are not expected to invent or discover these tools, but instead to determine with instructor guidance how these tools are used and how to interpret these representations. For example, how does a vector representation of forces describe interactions the object is involved in, and what do these forces allow us to infer about the current state of the object and its future behavior? Second, students are expected to be involved in the interpretation of these representational tools and drawing inferences from them as they pertain to physical laws. Third, students are expected to then deploy these established basic conceptual models by extending them to novel situations. Finally, students are expected to communicate basic conceptual models. This promotes greater expertise with the models when presenting to others and facilitates competence in scientific communication skills.

5.2.3.2 Studio format

MI is designed for implementation in a studio-format classroom. In studio physics classrooms students are able to flexibly engage in various types of activities, which may include labs, conceptual reasoning, or problem-solving activities. At Florida International University (FIU), the MI classroom integrates both the lecture and lab components of the introductory physics course and meets for a total of six hours per week across three days. Typically, students work in small groups of three to complete in-class activities. This small group work is summarized on small portable whiteboards. These whiteboards are then presented in larger group "board meetings" where all students in the class actively participate.

5.2.3.3 Small group participation

During the small group component, students work on model-building activities. In these groups, students begin the process of reaching consensus by creating whiteboards for sharing or "publishing" their lab results and/or solutions to problems. The instructor's role is to circulate through the classroom, asking questions, introducing new content, and examining the whiteboards that are being prepared. This small group work allows students to work together on a model-building activity, generate conceptual models, and practice communicating scientific information in a relatively 'low-stakes' setting.

5.2.3.4 Large group participation: The "Board Meeting"

The practice of having students first work in small groups and then present their outcomes to a larger group provides students with multiple opportunities to negotiate the use of conceptual models. The board meetings involve all students in the class gathering in a circle such that every member can see every other member and every groups' boards. During the board meeting, the instructor assumes the role of disciplinary expert and guides the discourse toward a shared conceptual model. Facilitating the discussion involves moderating the groups' whiteboard presentations, addressing student questions, and helping groups clarify their presentations and understanding. The instructor's guidance during the board meetings relies heavily on providing student groups with formative feedback. The explicit goal of these board meetings is to reach consensus regarding the conceptual models. In addition to the explicit goals, tacit goals include establishing the norms of a discourse community and encouraging students to utilize scientific argumentation strategies (Passmore & Svoboda, 2012). These strategies include supporting claims with evidence and reasoning based on the shared conceptual models.

5.2.3.5 Pairing large and small group interactions

The combined interaction structure is designed to elicit target conceptual models. The structure of these interactions also mimics the structure of science in general and physics in particular as practiced in a research setting. Students work in small research groups, building up and synthesizing the conceptual model that is subsequently 'published' at the board meeting, much like a scientific meeting. Both the small and large group settings rely on the pedagogical skill of the instructor. In MI-like environments (which are less 'instructor-centered' than traditional classrooms), the trajectory of the learning takes varied paths based on the input of the participants. For this reason, the curriculum and pedagogy of MI are less like a script for an actor to follow, and more like a set of guidelines for an improvisational comedienne.

5.2.3.6 Impact on student outcomes

The combination of curriculum materials designed to recursively implement the modeling cycle and a learning environment and pedagogy that are similarly supportive have been shown to be effective at promoting learning. Like other transformed curricula in university physics, MI promotes both conceptual understanding and student success in introductory physics (Brewe et al., 2010b). A survival analysis suggests that the increased success rate in introductory physics is not a result of lowered standards, as students from MI classes showed equivalent likelihood of success in completing a major in physics as students from lecture classes (Rodriguez et al., 2016). MI students also report improved attitudes about learning physics (Brewe et al., 2013, 2009) and these attitudinal shifts are equitable in terms of ethnicity (Traxler and Brewe, 2015). The group interactions in a MI class promote more well-developed classroom networks (Brewe et al., 2010a), and these networks are known to facilitate retention in physics courses (Zwolak et al., 2017). Positive shifts in self-efficacy associated with participating in MI have been documented, (Sawtelle, Brewe, & Kramer, 2010) although not consistently (Dou et al., 2016). We are in the process of studying qualitatively the construction of a conceptual model in MI (Sawtelle & Brewe, Under Review) and investigating students' representational choices in problem solving (McPadden and Brewe, 2017). These studies are consistent with students constructing and using conceptual models to solve problems and analyze physical systems. The successes coming from the MI classroom motivate our current research into the neurobiological mechanisms of reasoning in physics.

5.2.4 Investigating Mental Model Development Using Neuroimaging

While prior assessments of MI's impact on students has typically focused on the social construction of conceptual models (Brewe, 2011, 2008; Sawtelle et al., 2012), here we consider MI's potential impact on mental models using brain imaging techniques. This study aimed to investigate brain activation during a physics reasoning task and changes in brain activation after MI course instruction relative to before such instruction. Previous neuroimaging studies have localized brain activity associated with reasoning across various modalities (e.g., mathematics, formal logic, and fluid reasoning; Arsalidou and Taylor, 2011, Prado et al., 2011, Prabhakaran et al., 1997), but no investigations have probed for such brain activity in the field of physics or across physics classroom instruction. Because of this, no standardized tasks have been adapted for the MRI environment to examine such brain activation. Therefore, as a first step, we sought to develop a novel neuroimaging paradigm to probe brain activity during physics reasoning. We focused the development of this task on mental model use during physics reasoning, as previous research has provide evidence that students' use a variety of mental models during conceptual physics reasoning (Hegerty, 2004; Nersessian, 1999). Thus, we adapted items from the well-known *Force Concept Inventory* (FCI; (Hestenes et al., 1992)) which is known to engage conceptual physics reasoning. FCI questions were modified to fit with the parameters of the MRI data collection, and to investigate physics reasoning, (see Section 5.3.2 for further details. Simultaneously, to facilitate formation of neuroanatomical hypotheses regarding the brain networks we might observe during physics reasoning, we conducted a neuroimaging meta-analysis (Bartley et al., 2018) of fMRI studies that investigated problem solving across a diversity of representation modalities. Briefly, the primary outcome of that meta-analysis was that similar reasoning tasks using mathematical, verbal, and visuospatial stimuli involving attention, working memory, and cognitive control, activated the dorsolateral prefrontal and parietal regions. Participants completed this physics reasoning task while undergoing functional magnetic resonance imaging (fMRI) scanning, both before (pre) and after (post) completing a physics course in order to investigate the putative impact of physics instruction on brain function. Driving this neuroeducation project were two main hypotheses: 1) This novel physics reasoning task would induce increased activity in brain regions previously associated with attention, working memory, and problem solving (e.g., lateral prefrontal and parietal regions), and 2) Activation patterns would differ from pre- to post-course, indicating that brain activity can be modified as a result of physics instruction.

A few prior studies have demonstrated that short- and long-term course instruction can impact brain function. Differences in brain function have been observed from pre- to post-course among students enrolled in a 90-day Law School Admission Test preparation course (Mackey et al., 2013). Mason and Just (2015) showed that providing information to research participants about mechanical systems while in the MRI scanner, which they called physics instruction, led to changes in knowledge representation during successive stages of learning. In a separate study, they were also able to use machine learning and factor analysis to identify neural representations of four physics concepts: motion visualization, periodicity, algebraic forms, and energy flow (Mason and Just, 2016). However, to our knowledge, this is the first neuroeducational study to consider the impact of a full, semester-long physics class on the brain.

5.2.4.1 Brief primer on neuroimaging studies

This manuscript is intended for an educational research audience, with the expectation that readers have not had extensive experience with neuroimaging as a research methodology. As such, this section provides a brief overview of neuroimaging studies, particularly fMRI. In neuroimaging studies, researchers develop an experimental task to isolate mental operations of interest that participants perform lying in a MRI scanner while a series of three-dimensional brain images are acquired. Typically, these brain images are acquired approximately every 2 seconds and are composed of small volume elements called voxels, which in this study measured 3.4 mm^3. Within each voxel, the blood's changing oxygen levels (known as the blood-oxygenation level-dependent [BOLD] signal) are measured. Task-related changes in the BOLD signal provide an indirect measure of brain activity. In one implementation of fMRI experimental design, brain images are collected in blocks. During 'active task' blocks, participants are presented a stimulus (e.g., a physics question) engendering cognitive processes of interest (e.g., physics reasoning) and are instructed to make a response using a MRI-compatible keypad. During carefully constructed 'control task' blocks, participants are also presented with stimuli and give responses; however, the stimuli presented do not engender the cognitive processes of interest. Contrasting active blocks with control blocks presumably isolates task-related brain activity associated with the cognitive processes of interest and excluding those common to both conditions (e.g., visual processing, word reading, button pressing).

Following data collection, fMRI data are processed to correct for in-scanner head movement and fitted to a standardized brain template to enable averaging over a group of participants. BOLD time series from each voxel are input into a general linear model including distinct regressors for various task events (and other known sources of noise) to characterize the degree to which variability in the BOLD signal correlates with those task events. Resulting beta weights from active and control task blocks can then be contrasted and significant differences are interpreted as differences in brain activity between blocks. This procedure is repeated for the BOLD time series across all voxels in the entire brain.

Additional multi-level modeling can be performed on these results, as was done in this study, to test for changes in brain activity across repeated measures (i.e., from pre- to post-instruction).

5.3 Methods

5.3.1 Participants

Participants were drawn from MI classes at FIU over the course of three years (academic years 2014-2017). We recruited 55 students (33 male, and 22 female) in the age range of 18-25 years old (mean ± SD: 20.1 ± 1.4). All participants were screened to be right-handed, not using psychotropic medications, and free of psychiatric conditions, cognitive or neurological impairments and MRI contraindications. Volunteers invited to participate had not previously taken a college physics course and met either a GPA (>2.24) or SAT Math (>500) inclusion criteria. These criteria were implemented to minimize between-participant variability that could confound brain measurements associated with the experimental conditions. Written informed consent to a protocol approved by the FIU Institutional Review Board was obtained from all participants. Imaging data were collected on a General Electric 3-Tesla Healthcare Discovery 750W MRI scanner located in the Neuroimaging Suite (NIS) of the Department of Psychology at the University of Miami (Coral Gables, FL). Each participant completed a 90-minute MRI scanning session at both a pre- and post-instruction time point. The pre-session scans were scheduled within the first four weeks of the semester and the post-session scans were completed in the first two weeks following the semester. All participants were compensated for their time participating in the MRI assessment ($50 for pre- and $100 for post-scans).

5.3.2 Physics Reasoning Task

We adapted a set of questions from the *Force Concept Inventory* (FCI) for presentation in the MRI scanner (**Figure 5.2A**). The FCI was chosen given the substantial amount of extant data from students in MI at FIU on this measure (Brewe et al., 2010b), established reliability measures (Lasry et al., 2011), and known time requirements (Lasry et al., 2013). The FCI is a 30 question, multiple choice conceptual survey of students understanding of Newtonian mechanics (Hestenes et al., 1992). Each question has five multiple choice options, one correct and four distractors which were originally generated from student responses to open-ended versions of the same questions. The questions present 'every-day scenarios', do not require any mathematical calculations, and are presented as text describing the scenario accompanied by a representational diagram. To ensure that MRI data collection sessions were manageable and well-tolerated by participants, we reduced the number of FCI questions from 30 to nine (FCI 2, 3, 6, 7, 12, 14, 27 and 29). These nine questions were selected to span a range of difficulty levels that were simultaneously challenging enough to tax the mental resources of participants, but not necessarily the most difficult items in the FCI, as determined by item response curves in Morris et al. (2012) (

Table 5.2). Additionally, because measurement of brain networks via fMRI require the repeated observations across multiple yet similar experimental trials, we sought to narrow the broad range of physics-related cognition being probed in this task and selected questions that required students to determine the trajectories and motion of objects as resulting from different scenarios and combinations of initial velocities and/or force configurations. Given technical constraints associated with the use of a four-button MRI-compatible keypad, the questions were modified by removing the least chosen of the five multiple choice options, as indicated by the item response curves of Morris et al. (2012). In the current neuroimaging task implementation, each question was parsed into three self-paced presentation phases; participants were allowed to control the timing of these phases. The first phase of the question involved presentation of the text describing the phenomena and an accompanying diagram. The second phase posed the question, and the third phase presented the multi-choice answer options. FCI responses were assessed for overall and item-specific accuracy.

In addition to FCI questions, participants answered a series of ‘control questions’ (**Figure 5.2B**), each of which had similar characteristics to the FCI questions in terms of reading requirements, visual complexity, and overall design. However, control questions did not inquire about physics-related content, instead these questions focused on reading comprehension and shape discrimination. Control questions allowed us to isolate cognitive processes presumably related to physics reasoning when contrasting FCI (‘active task’) versus control questions (‘control task’).

FCI and control questions were presented in pseudo-random orders within three task runs. Each question was followed by 20 seconds of ‘rest’, during which participants maintained their gaze on a fixation cross centrally projected on the screen. These three runs lasted approximately six minutes each. Participants received instruction and practice on the task in a carefully managed mock scanner training session to ensure correct performance during the MRI session. In addition to acquainting participants to the task, the mock scanner also allows participants to experience what the actual MRI scan will be like.

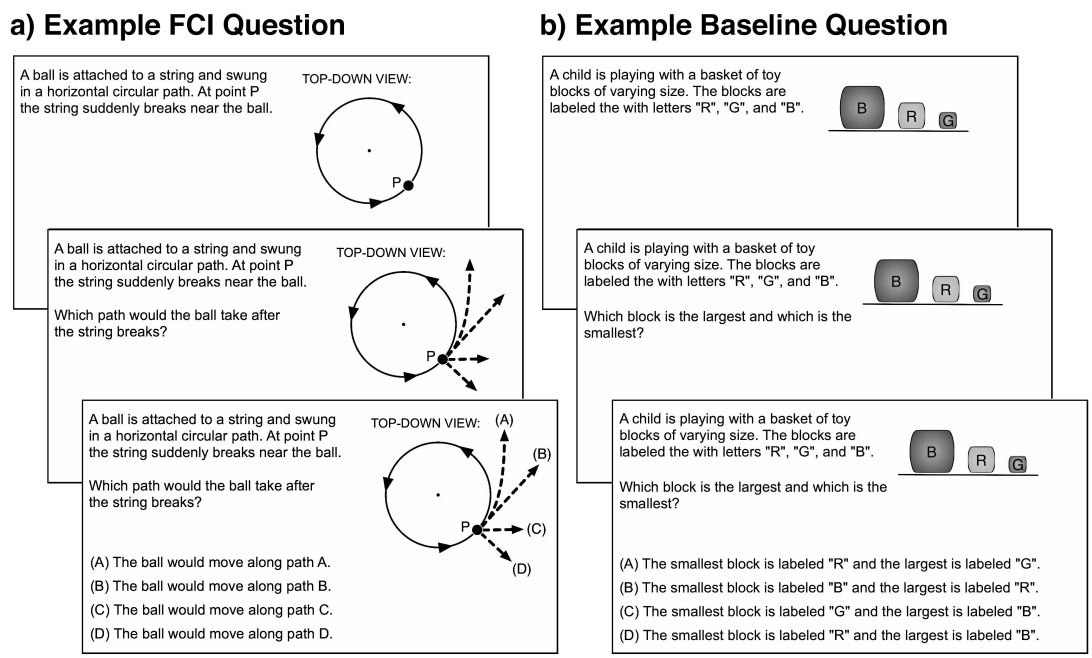


Figure 5.2. fMRI Task. Example items from the physics reasoning fMRI task. A) FCI questions described a physical scenario using pictures and words and then asked a physics question followed by four potential answers. B) Control question shared basic visual and linguistic features with FCI questions, however control questions did not ask students to engage in physics reasoning.

5.3.3 Data Analysis

Details on fMRI data acquisition parameters can be found in the supplementary materials. Prior to analysis, the data were preprocessed using commonly used neuroimaging analysis software packages: FSL (FMRIB Software Library, www.fmrib.ox.ac.uk/fsl) and AFNI (Analysis of Functional NeuroImages, http://afni.nimh.nih.gov/afni). Standard fMRI preprocessing procedures involved motion correction to remove signal artifacts associated with head motion, high-pass filtering to remove low frequency trends in the signal associated with non-brain noise sources (i.e. cardiac or respiratory), and spatial smoothing to increase signal to noise ratio during analysis. The data were then mapped to a standardized brain atlas (MNI152) to allow for group-level assessments.

We conducted two primary analyses to identify: 1) brain regions linked with physics reasoning (task effect) and 2) changes in brain activity associated with physics instruction (instruction effect). To delineate brain regions linked with physics reasoning at the pre-instruction time point, each preprocessed fMRI data set was input into a voxel-level General Linear Model (GLM) including regressors for the FCI and control task conditions (and various nuisance signals). Contrast images were created for each participant by subtracting the beta weights associated with the control questions from those for the FCI questions representing the degree to which each voxel responded more during physics reasoning as compared to the control condition (FCI>control). These participant-level contrast images were then input into a group-level, one-sample *t*-test and significant physics reasoning-related brain activations were defined using a threshold of $P_{corrected} < 0.05$ ($P_{\text{voxel-level}} < 0.001$, family-wise error [FWE] cluster correction). To delineate brain regions showing physics reasoning-related activation changes following a MI course, the participant-level FCI>Control task contrast images (described above) from the pre- and post-instruction data collection sessions were input into a group-level, paired samples *t*-test. Both Pre>Post and Post>Pre contrasts were computed and significant instruction-related brain activity changes were defined using a $P_{corrected} < 0.05$ threshold ($P_{\text{voxel-level}} < 0.001$, FWE cluster correction). Follow up correlational analyses were also conducted between the BOLD signal change across instruction (Post > Pre) in the four largest significant clusters ($\geq$ 1000 voxels) identified in the instruction effect analysis described above and accuracy post-instruction on the FCI using $P < 0.0125$, Bonferroni corrected. Because the clusters probed showed significant extent across multiple brain areas, BOLD signal was extracted from spherical seeds centered at the peaks z-score of each cluster.

5.4 Results

5.4.1 Accuracy

Table 5.2 includes the accuracy results of student responses for the nine questions in the pre and post-instruction scans along with item difficulties based in classical test theory, Morris et al. (2012). A paired-samples t-test was conducted to compare post- versus pre-instruction means. Cohen's *d*, was calculated to identify the magnitude of the effect, and 95% confidence intervals on the effect. The results of the t-test ($t(55) = 6.31$, $p < 0.001$) and Cohen's d ($d = 0.84$) with a 95% confidence interval of 0.45 – 1.23 indicate with a high degree of confidence that response accuracy increased after instruction. These results are consistent with prior results examining increased FCI accuracy after course instruction (Brewe et al., 2010). Furthermore, these accuracy results from participants in the scanner are in line with the classical test theory item difficulty (outside the scanner performance), where difficulty is calculated as the average score on a particular item.

Table 5.2. Overall and individual item accuracy for pre and post instruction FCI questions in the scanner. Item difficulty measures from Morris et al. (2012) are included for comparison.

FCI Question	Pre %	Post %	Change (Post-Pre)	Item Difficulty (Morris et al., 2012)
2	29.5%	39.3%	+9.8%	34.6%
3	42.6%	58.9%	+16.3%	51.5%
6	78.7%	78.6%	-0.1%	73.6%
7	54.1%	71.4%	+17.3%	66.4%
8	39.3%	46.4%	+7.1%	50.4%
12	45.9%	69.6%	23.7%	65.2%
14	24.6%	41.1%	16.4%	39.5%
27	44.3%	46.4%	2.1%	59.4%
29	42.6%	85.7%	43.1%	50.8%
Total	44.6%	59.7%	15.1%	

5.4.2 Task Effect

MI students exhibited physics reasoning-related brain activity (FCI>Control) at the pre-instruction time point in four general brain areas, the prefrontal cortex, the parietal cortex, the temporal lobes, and the right cerebellum (**Figure 3** red; **Table 5.3**). More specifically, in the prefrontal cortex (PFC), activation peaks were observed in the left superior frontal gyrus (SFG), dorsomedial PFC (dmPFC), bilateral dorsolateral PFC (dlPFC), inferior frontal gyri (IFG), and orbitofrontal cortex (OFC). Within the posterior parietal cortex, brain activity was observed bilaterally in the supramarginal gyri, intraparietal sulcus (IPS), and angular gryi. Large bilateral clusters of activation during physics reasoning were also observed in middle temporal (MT) and medial superior temporal (MST) areas. These same patterns of task-related brain activity from the pre-instruction stage were also observed when performing a similar assessment at the post-instruction stage (data not shown).

5.4.3 Instruction Effect

Significant increases in brain activity following instruction (Post > Pre) were observed within prefrontal and parietal cortices (**Figure 5.3** blue; **Table 5.4**). In particular, three clusters of increased PFC activity were identified in the left dlPFC along the inferior precentral sulcus, and bilaterally in the frontal poles. Parietal areas demonstrating increased activation after instruction were located in the posterior cingulate cortex (PCC) extending into retrosplenial cortex and the precuneus and in the left angular gyrus. No brain regions showed significantly more task-related activity at the pre-instruction stage as compared to post-instruction (Pre > Post). Follow up correlation analysis between the left PCC, left angular gyrus, left orbital frontal pole, and left DLPFC and accuracy on the FCI yielded no significant correlation (r_{pcc} = -0.12, $p_{corrected}$ = 1; r_{ag} = -0.07, $p_{corrected}$ = 1; r_{ofc} = -0.01, $p_{corrected}$ = 1; r_{dlpfc} = 0.02, $p_{corrected}$ = 1).

Table 5.3. Task effects: Coordinates of brain activity associated with the FCI>Control task. Cluster region labels are based off those reported by the IBASPM116 Human Brain Atlas. Center of mass coordinates for the contrast FCI>Control are reported in MNI space.

Regions Within Cluster	Cluster Size (mm^3)	Center of Mass (MNI space)			Mean Z Score
		X	Y	Z	

Left DLPFC, Left Superior Frontal Gyrus, Left Inferior Frontal Gyrus, and Left Lateral Frontopolar Cortex	64856	-36	26	28	4.62
Left Supramarginal Gyrus, Left Inferior Parietal Lobule, Left Angular Gyrus, and Left Superior Parietal Lobule	40016	-48	-50	42	4.88
Right Inferior Parietal Lobule, Right Supramarginal Gyrus, and Right Superior Parietal Lobule	21560	52	-36	44	4.82
Right Medial Temporal Area, Right Inferior Temporal Gyrus, Right Occipital Temporal Gyrus, Right Angular Gyrus	20616	52	-60	0	4.34
Right Inferior Frontal Gyrus, Right DLPFC, and Right Lateral Frontopolar Cortex	17928	50	26	12	4.05
Left Medial Temporal Area, Left Inferior Temporal Gyrus, Left Middle Occipital Gyrus	15176	-54	-64	-4	4.78
Right Cerebellum	7968	34	-72	-44	4.20

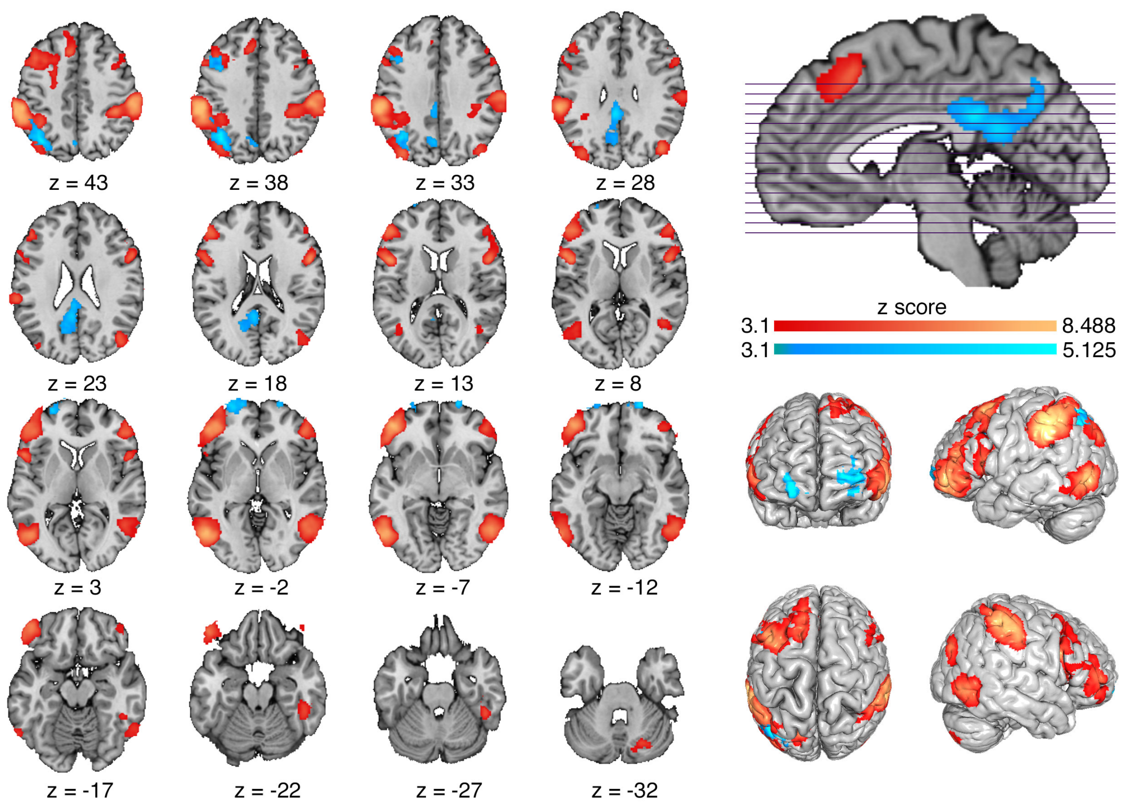


Figure 5.3. Physics Reasoning and Learning-Related Brain Activity. Group-level fMRI results. (Red) Task effect: Brain regions showing increased activity during the

physics reasoning task (FCI>control) at the pre-instruction stage. (Blue) Instruction effect: Brain regions showing increased activity at the post- relative to pre-instruction (Post>Pre) scan during the physics reasoning task.

Table 5.4. Instruction effect: Coordinates for brain regions showing greater activity (Post>Pre) following task instruction. Cluster region labels are based off those reported by the IBASPM116 Human Brain Atlas. Center of mass coordinates for the contrast Post>Pre are reported in MNI space.

Regions Within Cluster	Cluster Size (mm^3)	Center of Mass (MNI space)			Mean Z Score
		X	Y	Z	
Left Precuneus, Left Posterior Cingulate Cortex, and Left Retrosplenial Cortex	9288	-6	-54	26	3.54
Left Angular Gyrus, Left Superior Parietal Lobule, Left Intraparietal Sulcus, and Left Supramarginal Gyrus	8040	-38	-66	42	3.74
Left Anterior Superior Frontal Gyrus and Left Orbital Frontal/Frontopolar Cortex	3336	-22	66	-2	3.56
Left DLPFC and Left Inferior Frontal Gyrus	1968	-44	14	36	3.54
Right Orbital Frontal/Frontopolar Cortex, Right Anterior Superior Frontal Gyrus	1264	20	68	-8	3.69

5.5 Discussion

This neuroeducational study represents an initial effort to understand how physics reasoning may translate to the level of brain function assessed by fMRI and how instruction brings about changes in brain activity. To this end, we have provided fMRI results of brain activation from two main assessments. First, we observed that the physics reasoning task (FCI>Control questions) was associated with increased brain activity notably in lateral prefrontal and parietal regions. Second, we observed that students who completed the MI course showed increased activation during the physics reasoning task after the course in the posterior cingulate cortex and frontal pole regions.

5.5.1 Accuracy and Physics Reasoning

Participant responses to the FCI questions in the scanner show accuracy that is in line with published item difficulties and post course improvement in accuracy are consistent with Brewe et al. (2010). This suggests that the MRI version of the task we developed is prompting physics reasoning that is consistent with that observed out of scanner environment. Effect sizes from pre- to post-instruction indicate similar performance on this task with modified FCI questions as on the full FCI. This improvement is indicative of a shift in physics reasoning as a result of instruction. We do not interpret these changes as recall effects for two reasons, the results of the FCI were not discussed with students, and the task itself was not identified as being derived from the FCI. Further, Henderson (2002) has shown that recall effects over the duration of a full semester are minimal. While accuracy is important for characterizing and to some degree validating the task that was developed for the fMRI environment, we did not expect accuracy to correlate with brain activity. Instead, physics reasoning, regardless of accuracy, is linked to brain activity.

5.5.2 Task Effect: Brain Activity Linked with Physics Reasoning

Our initial analysis identified brain activity among college students associated with physics reasoning (FCI > control) in lateral prefrontal and parietal regions. One interpretation is that activity in these regions supports cognitive processes critical for answering physics reasoning problems such as attention, working memory, spatial reasoning, and mathematical cognition. More specifically, the lateral PFC's role in executive functions such as working memory and planning are well-characterized

(Bressler and Menon, 2010) and these areas are important in manipulating representations in working memory and reasoning (Andrews-Hanna, 2012; Barbey et al., 2013). Lateral parietal regions are involved in motor functioning as well as spatial reasoning, mathematical cognition, and attention (Wendelken, 2015). Such an interpretation is reasonable in the context of the current task which likely involves generating mental simulations and representations in the service of identifying the correct answer choice. From a large-scale brain network perspective, the brain regions showing physics reasoning-related activation resemble one commonly observed functional brain network known as the central executive network (CEN). The CEN, consisting of lateral prefrontal and parietal regions (Bressler and Menon, 2010), is generally associated with externally oriented attentional and executive processes (e.g., working memory, response selection, and inhibition; (Cole and Schneider, 2007; Seeley et al., 2007).

The task-related brain regions we observed were generally similar when separately considering data collected during the pre- and post-instruction scans. While speaking to the consistency of such brain activity, this analysis is not intended to determine which brain regions differ as a function of completing a MI course (see below). We suspect that such task-related brain activity would be similar among students in other instructional environments.

5.5.3 Instruction Effect: Changes in Brain Activity Post-instruction Versus Pre-instruction

Our second analysis identified increased brain activity among students completing the physics reasoning task after taking a MI course (Post > Pre) in the posterior cingulate cortex, frontal poles, dlPFC, and angular gyrus. These brain regions (PCC, angular gyrus) overlap with regions of another commonly observed large-scale functional brain network known as the default-mode network (DMN). The DMN, consisting of posterior cingulate cortex (PCC), angular gyri, medial PFC, and middle temporal gyri (Laird et al., 2009; Raichle et al., 2001), is generally associated with internally oriented cognitive processes (i.e., self-reflection, mind wandering, autobiographical memory, planning; (Buckner et al., 2008). However, other lines of evidence also implicate DMN involvement in complex tasks such as narrative comprehension (Simony et al., 2016), semantic processing (Binder et al., 2009; Binder and Desai, 2011) or the generation and manipulation of mental images (Andrews-Hanna, 2012). In the context of the current task, one interpretation is that students may generate mental images to simulate events and formulate predictions. Additionally, post-instruction increase in DMN activity was observed during physics reasoning (which we show is supported by the CEN), and such coupling between the DMN and CEN during cognition has been hypothesized to arise during controlling attentional focus, thereby aiding in efficient cognitive function (Leech & Sharp, 2014).

Other brain regions showing greater activation during physics reasoning after the MI course included the dlPFC and the frontopolar cortex. The frontopolar cortex is a component of a decision-making network often involved with learning (Koechlin and Hyafil, 2007). The dlPFC is critically linked with the manipulation of verbal and spatial information in working memory (Barbey et al., 2013). Given previous links with, for example, mental simulation, working memory, mathematical calculations, and attention, we speculate that post-instruction increased activity in the PCC, angular gyrus, dlFPC and frontal pole may reflect enhanced mental operations and/or models involved with physics reasoning and/or generation of predictions about physical outcomes.

The PCC, left angular gyrus, left frontal pole, and left DLPFC were the four regions of greatest extent to show increased activity (Post > Pre), however, we did not see correlation between change in activity within these areas and accuracy on the FCI after instruction. The FCI is a cognitively demanding task which includes intuitive but wrong answers. Thus, it may simply be that even wrong answers on the FCI require significant mental effort. Inaccurate physics reasoning likely still involves many of the same mental operations successful physics reasoning does (i.e., mental imagery, visualization, prediction generation, and decision making, to name a few). Measures of accuracy in and of themselves may not display a simple one-to-one relationship with changes in brain activity across instruction. Rather, these changes in brain activity may be related to more complex behavioral changes in how student's reason through physics questions post-relative to pre-instruction. These might include shifts in strategy or an increased access to physics knowledge and problem solving resources.

We posit that the observed pre to post-instruction changes in brain activation during physics reasoning are consistent with what one may expect to observe as students develop refined mental models during classroom learning. Physics reasoning, regardless of an individual's familiarity with the material, is a process continually scaffolded by mental model use (Giere, 2005; Koponen, 2006; Nersessian, 1995, 1999, 2002a, 2002b), and effective physics learning is engendered by building and deploying strategies to appropriately implement mental models during reasoning (Hestenes et al., 1987). In this study, we framed our exploration of learning-induced changes in brain activity in the context of the MI classroom because this pedagogical approach has been shown to effectively encourage the development and flexible implementation of models during physics reasoning (Brewe, 2008; Brewe et al., 2010b). Our experimental results do not go as far as to implicate MI as any more or less effective than other instructional strategies at supporting instructional-related changes in student's brain networks. However, if we accept that physics reasoning inherently relies on mental model use, we can begin to consider a more truly neuroeducational interpretation of physics learning in which shifts in network engagement across instruction bring about student conceptual change. Characterizing these neurobiological changes may ultimately help researchers and educators understand which instructional strategies may best support successful model development. We hold that the mental models student's deployed at the beginning of the semester during reasoning, upheld by a variety of CEN-supported attentional and executive processes, shifted after instruction, as evidenced by student's overall increased accuracy during reasoning. This instruction-induced shift in model use promoted increased involvement from key DMN and CEN regions within reasoning. This study represents an initial step in neuroeducational research demonstrating that such shifts, indicative of learning, are measurable and detectable using non-invasive brain imaging techniques. Additional work is needed to understand the relationship between external conceptual models as studied in science education, with mental models and related cognitive constructs as studied in neuroimaging literature.

This project has several limitations. First, we focused on the MI class and did not assess the brain activity of students from traditional lecture course sections or other active learning environments. Based on the data presented, we do not make claims that MI is a better or the only instructional tool capable of inducing brain network alterations. Rather, in the current study, we used MI as an exemplar case. It remains to be determined if different pedagogies differentially influence how physics reasoning-related brain networks develop. As noted above and consistent with recommendations (Scott Freeman et al., 2014), we will explore this in the future and a future direction could investigate differences among active learning formats. Second, these analyses addressed brain activation and did not consider correlation with other behavioral measures, such as mental rotations, science anxiety, or academic performance measures would could further aid in the interpretation of these fMRI outcomes. Third, consideration of potential differences between female and male students remains for future investigations.

Notwithstanding these limitations and future direction, these preliminary outcomes implicate brain regions linked with physics reasoning and, critically, suggest that brain activity during physics reasoning is modifiable over the course of a semester of physics instruciton. Further work should investigate differences between MI and lecture instruction, as well as addressing differences among different active learning strategies across disciplines. Studying active learning broadly has the potential to more clearly elaborate how these pedagogies impact student learning and brain function.

5.6 Supplemental Material

5.6.1 Data Acquisition

Imaging data were collected on a General Electric 3 Tesla Healthcare Discovery 750W MRI scanner using a 32-channel phased-array radio frequency coil. High-resolution T1-

weighted series were acquired for anatomical reference with a 3D fast spoiled gradient recall brain volume (FSPGR BRAVO) sequence. T1-weighted sagittal slices were acquired with TI = 650ms, bandwidth = 25.0kHz, flip angle = 12°, voxel dimensions = 1×1×1 mm, and slice thickness = 1.0mm. Functional data were acquired using an interleaved gradient-echo, echo planar imaging (EPI) pulse sequence (TR/TE = 2000/30ms, flip angle = 75°, field of view = 220x220 mm, matrix size = 64x64, voxel dimensions = 3.4×3.4×3.4 mm, slice spacing = 0 mm, with a bottom-up interleaved acquisition). A total of 42 axial oblique slices were collected for each participant. These slices were acquired at a 30° angle from the anterior commissure/posterior commissure plane so as to reduce signal dropout due to proximity to the sinus cavity.

5.6.2 Data Preprocessing and Analysis

Preprocessing and analysis were carried out in FSL (FMRIB, www.fmrib.ox.ac.uk/fsl) for this study. The AFNI software library (http://afni.nimh.nih.gov/afni) was used to perform initial image orientation prior to preprocessing: the first five frames of each functional run were discarded to allow for stabilization of the MR signal across the brain, and, to ensure L/R orientation consistency across all volumes, spatial orientation and stereotactic origin for functional and structural images were matched to that of the standardized MNI152 template. These data were then fed into FSL's FEAT tool. Preprocessing involved rigid-body motion correction of functional runs by using FSL's MCFLIRT. Anatomical and functional images were skull stripped with BET and functional volumes were spatially smoothed using a 5mm Gaussian kernel. Functional images were then high-pass filtered at a threshold of 110s. Affine transformations (12-

degree-of-freedom) were then performed using FLIRT to co-register functional series with each participant's structural volume. All images were then transformed into standardized MNI152 space using non-linear resampling in FNIRT.

Each FCI and control question was modeled as a single block in which block duration was given by the onset of each question to the onset of a central concluding fixation cross. The fixation cross was presented between each question and allowed for the brain's hemodynamic response to return to baseline before beginning the next question. All questions (FCI and Control) were self-paced: all question text was replaced by the central fixation cross when the student selected their answer choice. Stimulus timing files were convolved with a Gamma function to model the brain's hemodynamic response and the first temporal derivatives of each stimulus timing file were computed. General linear modeling (GLM) was performed in FSL using FEAT to assess the contrast of FCI>Control. The GLM design matrix contained regressors for FCI and Control questions, as well as regressors of no interest for the stimulus derivatives to account for any offsets in peak BOLD response, as well as six standard motion parameters (3 translation, 3 rotation). Additionally, image scrubbing was performed at the subject-level analyses to discard volumes containing motion greater than .35mm Framewise Displacement.

Chapter 6

Conclusions and Future Work

6.1 Summary of Findings

The work presented in the previous chapters aimed to gather and assess evidence of human learning and knowledge organization as measured by the functional magnetic resonance imaging of student brain activity across semester-long university-level introductory physics learning experiences. This project sought to extend neuroimaging advances into the realm of education research by investigating the socially and ecologically relevant challenges that face physics education today. Each study in this collection of work contains its own concluding remarks; however, I will attempt to frame these findings in the overall context of the larger project here.

In the first study, we comprehensively synthesized a large corpus of neuroimaging literature that had previously been only considered separately. Through eight separate quantitative coordinate-based meta-analyses we identified convergent brain activity associated with human problem solving across its multiple forms. The major findings from this set of investigations were that 1) problem solving engages the central executive network (CEN) across a wide range of contexts, 2) specific CEN sub-networks separately support mathematical, verbal, and visuospatial problem solving variants, and 3) a convergent core neural system subtended all types of problem solving. Based on these results we proposed a model of general problem solving-related brain function that described cross-network cooperation between regulatory, perceptual, and context-specific circuits to carry out the iterative cognitive steps needed to solve problems. These observations provided specific neuroanatomical predictions that we applied to inform and elucidate the physics problem solving-specific fMRI analyses of Chapter 4. Additionally, the understanding of problem solving-related brain function across knowledge domains gained this study can inform innovative neuroeducation investigations on how students may acquire problem solving skills across classroom instruction.

The following section presented the overview and implementation of just such an investigation. In Chapter 3, I presented an overview of a very large longitudinal data collection project, entitled *Exploring the Neural Mechanisms of Physics Learning*, which was designed to gather and assess evidence of human learning, as measured by the fMRI of student brain activity, across semester-long university-level physics classroom instruction. In this section I described the creation of three novel neuroimaging paradigms to measure brain networks associated with physics problem solving, physics memory retrieval, and general reasoning. I also presented a summary of recruitment and data acquisition procedures that accompanied the facilitation of this project through completion. Pre- and post-instruction fMRI and behavioral data sets were acquired from 121 physics students who completed 229 total MRI scans. Analyses of data acquired as part of this broader project are ongoing (see §6.2 Future Work for details) and the following chapters presented the first set of publications that resulted from this larger project.

To our knowledge, the brain activity underlying physics problem solving in introductory physics students has never before been observed. Thus, the natural first goal in the larger neuroeducation project was to characterize the neural mechanisms of physics problem solving after University-level instruction had already occurred. Towards this end and in Chapter 4, we assessed the post-instruction brain function of 107 students during physics reasoning, investigated how these networks shifted across different stages of problem solving, and probed for putative relationships between brain function and accuracy, difficulty, strategy, and students' conceptualization of physics ideas. Primary findings resulting from this set of analyses were that 1) physics problem solving is supported by the CEN (similar to the problem solving observations of Chapter 2) and additionally engages V5/MT+, an area linked to motion visualization, 2) different stages of physics problem-solving engage different brain networks, with solution generation relying on critical interactions between the default mode network (DMN) and CEN that may indicate episodic and semantic memory retrieval processes during physics reasoning, consistent with the constructivist theory of learning. Additionally, while 3) problem accuracy did not modulate brain activity, 4) variance in conceptual approach during physics reasoning characterized brain differences, and these in turn impacted success rate. Specifically, students who applied more coherent physics conceptions showed enhanced frontal and V5/MT+ engagement during reasoning, whereas those who held less coherent physics conceptions engaged relatively more visual and salience network areas during problem solving. These findings are consistent with the "resources" framework of physics thinking and we find evidence that brain differences during physics reasoning are observable along an axis knowledge compilation, coherence, and robustness.

In our opinion, this study exemplifies the potential of neuroeducation research to provide valuable insight into student classroom learning. Guided by education research and theory, our neuroimaging results indicate student's conceptual foundations reveal significantly more about their ability to succeed than simply counting right vs. wrong answers does. A focus on accuracy alone over-simplifies the complex processes that are engaged during physics reasoning. Instead, physics instruction may benefit students by explicitly instructing them on how students select, link, and reorganize their physics conceptions.

Finally, Chapter 5 presents findings on the functional reorganization of physics problem solving-related brain as resulting from University-level classroom learning. Motivated by the assertion that science involves the iterative deployment, validation, and revision of models (Brewe, 2008; Hestenes, 1987), this investigation sought to provide neurobiological evidence of physics learning through the explicit development of physics mental models. Modeling Instruction is a curriculum and pedagogy that explicitly structures class time around providing students with opportunities to build, test, and revise physics models, and has been shown to effectively encourage the development and flexible implementation of models during physics reasoning (Brewe, 2008; Brewe et al., 2010b). Because of this, we focused our investigations in this study on pre- and post-instruction physics problem solving-related fMRI from Modeling Instruction students. Students who completed the Modeling Instruction course 1) showed significantly increase accuracy during physics reasoning after the course, indicating they learned how to solve physics problems, 2) engaged physics problem-related brain activity in the CEN-V5/MT+ network, in agreement with the findings of Chapter 4, and 3) demonstrated large-scale network reorganization during reasoning after Modeling Instruction, with Post > Pre physics problem solving-related brain activity being linked with increased activity in the DMN. We note that these results are consistent with the CEN-DMN coherence observed during the reasoning and answer making stage of problem solving, as reported in Chapter 4. We posit that these Pre- to Post-instruction changes in brain activation during physics reasoning are consistent with what one may expect to observe as students develop refined mental models during classroom learning.

6.2 Future Work

The studies presented in this dissertation constitute the first of several ongoing investigations resulting from the broader *Exploring the Neural Mechanisms of Physics Learning* project. These investigations involve analyses of fMRI data collected across the retrieval, general reasoning, and resting-state paradigms, and explore correlations between these brain networks and behavioral measures such as STEM anxiety, GPA, and course grade. Group comparisons across Lecture and Modeling Instruction class types are being considered to assess any potential effects pedagogy may have on the development of brain networks across learning. Additionally, gender effects associated with reasoning and retrieval-related brain networks are being investigated. Dynamic functional connectivity, as measured via sliding window graph theory, is also being used as a methodology to investigate how individual difference measures of class performance may load onto different task-related brain networks.

Through the collection of work presented in this dissertation, we have provided neurobiological evidence of physics problem solving and learning as measured across classroom instructional environments. Future work will continue to investigate how instructional environments, group differences, or behavioral factors may impact student brain function. This novel neuroeducation project is the first of its kind to consider how learning environments drive functional reorganization of brain networks in physics students. We hope that the outcomes of the project will continue to have broad applicability to how we understand human learning in STEM.

Appendices

A.1 Neuroimaging Studies Included in the Problem Solving Meta-Analyses

The following are supplemental materials published alongside the text and figures presented in Chapter 3 of this dissertation.

Table A.1. Published neuroimaging studies included in the problem solving meta-analyses. Table a) lists the mathematical problem solving experiments included in the mathematical domain analysis, table b) lists the verbal problem solving experiments included in the verbal domain meta-analysis, table c) lists the visuospatial problem solving experiments included in the visuospatial domain meta-analysis, and table d) lists the problem solving experiments included in the problem demand meta-analysis.

a) Mathematical Problem Solving Experiments

Publication	*Contrast*	*#Foci*	*Subjects*	*Paradigm Classification*	*Stimulus Type*	*Task Performed*	*Contrast Classification*	*Imaging Modality*
Andres et al., 2011	1. Multiply > Subtract	7	10	Number Operand	Numbers, Letters	Multiplication, Subtraction	Problem Solving Type I > Problem Solving Type II	fMRI
Audoin et al., 2005	1. PASAT - Repeat, Healthy Controls	45	18	PASAT / PVSAT	Auditory numbers	Addition	Problem Solving > Baseline	fMRI
Chochon et al., 1999	1. Multiplication vs. Control	12	8	Number Operand	Numbers, Letters	Multiplication, Subtraction	Problem Solving > Baseline	fMRI
	2. Subtraction vs. Control	14		Number Operand	Numbers, Letters	Multiplication, Subtraction	Problem Solving > Baseline	fMRI
	3. Multiplication vs. Digit Naming	4		Number Operand	Numbers, Letters	Multiplication, Subtraction	Problem Solving > Baseline	fMRI

	4. Multiplication vs. Comparison	1		Number Operand	Numbers, Letters	Multiplication, Subtraction	Problem Solving > Baseline	fMRI
	5. Subtraction vs. Digit Naming	11		Number Operand	Numbers, Letters	Multiplication, Subtraction	Problem Solving > Baseline	fMRI
	6. Subtraction vs. Comparison	13		Number Operand	Numbers, Letters	Multiplication, Subtraction	Problem Solving > Baseline	fMRI
	7. Subtraction vs. Multiplication	4		Number Operand	Numbers, Letters	Multiplication, Subtraction	Problem Solving Type I > Problem Solving Type II	fMRI
Christodoulou et al., 2001	1. Healthy Controls: mPASAT > control	24	7	PASAT / PVSAT	Auditory numbers	Addition	Problem Solving > Baseline	fMRI
Cowell et al., 2000	1. Simple Mental Calculation Activations	6	12	Number Operand	Words	Addition, Subtraction, Multiplication, Division	Problem Solving > Baseline	PET
De Pisapia et al., 2006	1. Multi-operand Mental Arithmetic	9	20	Number Operand	Number, Symbols	Addition, Subtraction, Multiplication	Problem Solving > Baseline	fMRI
Dehaene et al., 1999	1. Exact Addition - Approximate Addition	7	7	Number Operand	Numbers, Math Symbols	Addition	Problem Solving Type I > Problem Solving Type II	fMRI

Delazer et al., 2003	1. Untrained Multiplication Set vs. Number Matching	13	13	Number Operand	Numbers, Math Symbols	Multiplication	Problem Solving > Baseline	fMRI
Delazer et al., 2005	1. New Strategy Problems vs. Number Matching	5	9	Additional PS Type	Number, Symbols	Multi-operand Algorithm	Problem Solving > Baseline	fMRI
	2. Trained Strategy Problems vs. Trained Drill Problems	6		Additional PS Type	Number, Symbols	Multi-operand Algorithm	Problem Solving Type I > Problem Solving Type II	fMRI
Fehr et al., 2007	1. Addition: Complex > Simple	17	11	Number Operand	Numbers, Math Symbols	Addition, Subtraction, Multiplication, Division	Complex > Simple	fMRI
	2. Subtraction: Complex > Simple	18		Number Operand	Numbers, Math Symbols	Addition, Subtraction, Multiplication, Division	Complex > Simple	fMRI
	3. Multiplication: Complex > Simple	9		Number Operand	Numbers, Math Symbols	Addition, Subtraction, Multiplication, Division	Complex > Simple	fMRI
	4. Division: Complex > Simple	15		Number Operand	Numbers, Math Symbols	Addition, Subtraction, Multiplication, Division	Complex > Simple	fMRI

Grabner et al., 2007	1. Multi-Digit Multiplication > Single-Digit Multiplication	15	12	Number Operand	Numbers, Equations	Multiplication Verification	Complex > Simple	fMRI
Gruber et al., 2001	1. Compound Number Calculation > Number Matching	7	6	Number Operand	Number, Symbols, Letters	Multiplication, Division	Problem Solving > Baseline	fMRI
	2. Simple Number Calculation > Number Matching	8		Number Operand	Number, Symbols, Letters	Multiplication, Division	Problem Solving > Baseline	fMRI
Hanakawa et al., 2003	1. Numerical Mental Operations > Number Repeating	9	16	Number Operand	Numbers	Addition, Subtraction, Multiplication, Division	Problem Solving > Baseline	fMRI
Hugdahl et al., 2004	1. Healthy Subjects: Mental Arithmetic - Number Vigilance Task	4	12	PASAT / PVSAT	Numbers	Addition	Problem Solving > Baseline	fMRI
Ischebeck et al., 2006	1. Multiplication Untrained vs. Number Matching	13	12	Number Operand	Numbers, Equations	Multiplication, Subtraction	Problem Solving > Baseline	fMRI

	2. Subtraction Untrained vs. Number Matching	21		Number Operand	Numbers, Equations	Multiplication, Subtraction	Problem Solving > Baseline	fMRI
	3. Subtraction Untrained vs. Multiplication Untrained	2		Number Operand	Numbers, Equations	Multiplication, Subtraction	Problem Solving Type I > Problem Solving Type II	fMRI
Ischebeck et al., 2009	1. Differences: Division > Multiplication	2	17	Number Operand	Numbers, Equations	Multiplication, Division	Problem Solving Type I > Problem Solving Type II	fMRI
Kawashima et al., 2004	1. Adults only: Addition Task - Fixation Control	10	8	Number Operand	Numbers, Math Symbols	Addition, Subtraction, Multiplication	Problem Solving > Baseline	fMRI
	2. Adults only: Subtraction Task - Fixation Control	8		Number Operand	Numbers, Math Symbols	Addition, Subtraction, Multiplication	Problem Solving > Baseline	fMRI
	3. Adults only: Multiplication Task - Fixation Control	10		Number Operand	Numbers, Math Symbols	Addition, Subtraction, Multiplication	Problem Solving > Baseline	fMRI
Kong et al., 2005	1. Addition Without Carrying vs. Rest	5	16	Number Operand	Numbers, Equations	Addition, Subtraction	Problem Solving > Baseline	fMRI

	2. Addition With Carrying vs. Rest	14		Number Operand	Numbers, Equations	Addition, Subtraction	Problem Solving > Baseline	fMRI
	3. Subtraction Without Borrowing vs. Rest	11		Number Operand	Numbers, Equations	Addition, Subtraction	Problem Solving > Baseline	fMRI
	4. Subtraction With Borrowing vs. Rest	10		Number Operand	Numbers, Equations	Addition, Subtraction	Problem Solving > Baseline	fMRI
	5. Main Effect of Arithmetic Type: Subtraction vs. Addition	5		Number Operand	Numbers, Equations	Addition, Subtraction	Problem Solving Type I > Problem Solving Type II	fMRI
	6. Main Effect of Procedure Complexity: Carrying/Borrowing vs. No Carrying/Borrowing	4		Number Operand	Numbers, Equations	Addition, Subtraction	Complex > Simple	fMRI
Krueger et al., 2008	1. Integral Calculus Equation Verification - Font Verification	12	18	Additional PS Type	Numbers, Math Symbols	Integral Calculus	Problem Solving > Baseline	fMRI
Kuo et al., 2008	1. Single Addition > Number Matching	13	11	Number Operand	Numbers, Math Symbols	Addition, Subtraction	Problem Solving > Baseline	fMRI

	2. Single Subtraction > Number Matching	17		Number Operand	Numbers, Math Symbols	Addition, Subtraction	Problem Solving > Baseline	fMRI
	3. Dual Addition > Number Matching	15		Number Operand	Numbers, Math Symbols	Addition, Subtraction	Problem Solving > Baseline	fMRI
	4. Dual Subtraction > Number Matching	21		Number Operand	Numbers, Math Symbols	Addition, Subtraction	Problem Solving > Baseline	fMRI
	5. Dual Operation > Number Matching	26		Number Operand	Numbers, Math Symbols	Addition, Subtraction	Problem Solving > Baseline	fMRI
Lazeron et al., 2003	1. PVSAT vs. Fixation	11	9	PASAT / PVSAT	Numbers	Addition	Problem Solving > Baseline	fMRI
	2. High Speed PVSAT vs. Low Speed PVSAT	10		PASAT / PVSAT	Numbers	Addition	Complex > Simple	fMRI
Lee, 2000	1. Multiplication > Subtraction	6	11	Number Operand	Numbers, Equations	Multiplication, Subtraction	Problem Solving Type I > Problem Solving Type II	fMRI
	2. Subtraction > Multiplication	8		Number Operand	Numbers, Equations	Multiplication, Subtraction	Problem Solving Type I > Problem Solving Type II	fMRI
Mainero et al., 2004	1. Healthy Controls: PASAT activations	37	22	PASAT / PVSAT	Auditory numbers	Addition	Problem Solving > Baseline	fMRI

Maruishi et al., 2007	1. Healthy Controls: PVSAT - Number Control Task	7	12	PASAT / PVSAT	Numbers	Addition	Problem Solving > Baseline	fMRI
Menon et al., 2000	1. Slow Presentation: 3-Operand Math Problems - Number Control Condition	16	16	Number Operand	Numbers, Math Symbols	Addition and Subtraction Verification	Problem Solving > Baseline	fMRI
	2. Slow Presentation: 2-Operand Math Problems - Number Control Condition	6		Number Operand	Numbers, Math Symbols	Addition and Subtraction Verification	Problem Solving > Baseline	fMRI
	3. Fast Presentation: 3-Operand Math Problems - Number Control Condition	5		Number Operand	Numbers, Math Symbols	Addition and Subtraction Verification	Problem Solving > Baseline	fMRI
	4. Main Effect of Operand	3		Number Operand	Numbers, Math Symbols	Addition and Subtraction Verification	Problem Solving > Baseline	fMRI
Molko et al., 2003	1. Healthy Controls: Calculation > Rest	11	14	Number Operand	Number, Symbols, Letters	Addition	Problem Solving > Baseline	fMRI

	2. Healthy Controls: Effect of Number Size During Exact Calculation	7		Number Operand	Number, Symbols, Letters	Addition	Problem Solving > Baseline	fMRI
Montojo and Courtney, 2008	1. Calculation with NMBR, RULE, BOTH switching > Calculation with HOLD for Number and Rule	6	16	Number Operand	Numbers	Addition, Subtraction	Complex > Simple	fMRI
	2. Main Effect: Calculation (NMBR Switching, RULE Switching, Switching BOTH Number and Rule)	7		Number Operand	Numbers	Addition, Subtraction	Complex > Simple	fMRI
	3. Main Effect: Event (all screens CUE, CALC, ANSW)	11		Number Operand	Numbers	Addition, Subtraction	Problem Solving > Baseline	fMRI

	4. Calculation Switching NMBR only > Calculation Switching RULE only	5		Number Operand	Numbers	Addition, Subtraction	Problem Solving Type I > Problem Solving Type II	fMRI
	5. Calculation Switching BOTH Number and Rule > Calculation Switching NMBR Only	5		Number Operand	Numbers	Addition, Subtraction	Problem Solving Type I > Problem Solving Type II	fMRI
	6. Calculation Switching BOTH Number and Rule > Calculation Switching RULE Only	8		Number Operand	Numbers	Addition, Subtraction	Problem Solving Type I > Problem Solving Type II	fMRI
Newman et al., 2011	1. Easy Number Problems - Fixation	9	15	Additional PS Type	Numbers	Algebra Problems	Problem Solving > Baseline	fMRI
	2. Hard Number Problems - Fixation	11		Additional PS Type	Numbers	Algebra Problems	Problem Solving > Baseline	fMRI

	3. Number Problems > Word Problems	6		Additional PS Type	Numbers, Words	Algebra Problems	Problem Solving Type I > Problem Solving Type II	fMRI
Pesenti et al., 2000	1. Addition vs. Rest	21	8	Number Operand	Number, Symbols	Addition	Problem Solving > Baseline	PET
	2. Addition vs. Comparison of Numerical Magnitudes	2		Number Operand	Number, Symbols	Addition	Problem Solving > Baseline	PET
	3. Addition vs. Characters Orientation	5		Number Operand	Number, Symbols	Addition	Problem Solving > Baseline	PET
Rickard et al., 2000	1. Conjunction: Calculation > Detect Ones and Calculation > Number Comparison	8	8	Number Operand	Numbers, Equations	Multiplication Verification	Problem Solving > Baseline	fMRI
Rivera et al., 2002	1. Healthy Controls: 2-Operand Calculation - Number Control Task	12	16	Number Operand	Numbers, Equations	Addition, Subtraction	Problem Solving > Baseline	fMRI

	2 Healthy Controls: 3-Operand Calculation - Number Control Task	9		Number Operand	Numbers, Equations	Addition, Subtraction	Problem Solving > Baseline	fMRI
Rosenberg-Lee et al., 2011	1. Subtraction: Calculation - Identification	4	20	Number Operand	Numbers, Equations	Subtraction Verification	Problem Solving > Baseline	fMRI
	2. Multiplication: Calculation - Identification	6		Number Operand	Numbers, Equations	Multiplication Verification	Problem Solving > Baseline	fMRI
	3. Division: Calculation - Identification	6		Number Operand	Numbers, Equations	Division Verification	Problem Solving > Baseline	fMRI
	4. Multiplication - Subtraction	3		Number Operand	Numbers, Equations	Multiplication Verification, Subtraction Verification	Problem Solving Type I > Problem Solving Type II	fMRI
	5. Multiplication - Addition	2		Number Operand	Numbers, Equations	Multiplication Verification, Addition Verification	Problem Solving Type I > Problem Solving Type II	fMRI
	6. Division - Multiplication	9		Number Operand	Numbers, Equations	Multiplication Verification, Division Verification	Problem Solving Type I > Problem Solving Type II	fMRI

Simon et al., 2002	1. Calculation vs. Calculation Control	23	10	Number Operand	Numbers, Letters	Subtraction	Problem Solving > Baseline	fMRI
	2. Calculation Only (regions active in calculation but not in five other non-calculation tasks)	1		Number Operand	Numbers, Letters	Subtraction	Problem Solving Type I > Problem Solving Type II	fMRI
Simon et al., 2004	1. Calculation Only (regions active in calculation but not in five other non-calculation tasks)	11	10	Number Operand	Numbers, Letters	Subtraction	Problem Solving Type I > Problem Solving Type II	fMRI
Stanescu-Cosson et al., 2000	1. Exact and Approximate Calculation vs. Letter Matching	16	7	Number Operand	Numbers, Letters	Addition	Problem Solving > Baseline	fMRI
	2. Calculation with Small Numbers vs. Letter Matching	7		Number Operand	Numbers, Letters	Addition	Problem Solving > Baseline	fMRI

	3. Exact Calculation > Approximation	12		Number Operand	Numbers, Letters	Addition	Problem Solving Type I > Problem Solving Type II	fMRI
Venkatraman et al., 2006	1. Peak Activations: Exact Addition in Base-7	18	20	Additional PS Type	Words spelling out numbers	Addition, Percent Estimation	Problem Solving > Baseline	fMRI
	2. Peak Activations: Percentage Estimation in Base-10	17		Additional PS Type	Words spelling out numbers	Addition, Percent Estimation	Problem Solving > Baseline	fMRI
Wood et al., 2008	1. NBT: Large Bisection Range > Small Bisection Range	18	17	Additional PS Type	Numbers	Number Bisection Task (NBT)	Complex > Simple	fMRI
	2. NBT: Decade Crossing > No Decade Crossing	17		Additional PS Type	Numbers	Number Bisection Task (NBT)	Complex > Simple	fMRI
	3. NBT: Large Problem Size > Small Problem Size	6		Additional PS Type	Numbers	Number Bisection Task (NBT)	Complex > Simple	fMRI
	4. NBT: Large Distance to Mean > Small Distance to Mean	5		Additional PS Type	Numbers	Number Bisection Task (NBT)	Complex > Simple	fMRI

Wu et al., 2009	1. Mental Arithmetic with Roman Numerals: Calculation - Identification	4	18	Number Operand	Arabic and Roman Numerals, Equations	Addition and Subtraction Verification	Problem Solving > Baseline	fMRI
	2. Mental Arithmetic with Arabic Numerals: Calculation - Identification	3		Number Operand	Arabic and Roman Numerals, Equations	Addition and Subtraction Verification	Problem Solving > Baseline	fMRI
	3. Mental Arithmetic: Arabic Numerals - Roman Numerals	2		Number Operand	Arabic and Roman Numerals, Equations	Addition and Subtraction Verification	Problem Solving Type I > Problem Solving Type II	fMRI
	4. Mental Arithmetic: Roman Numerals - Arabic Numerals	6		Number Operand	Arabic and Roman Numerals, Equations	Addition and Subtraction Verification	Problem Solving Type I > Problem Solving Type II	fMRI
Zago et al., 2001	1. Computation vs. Number Reading	14	6	Number Operand	Numbers	Multiplication, Read	Problem Solving > Baseline	PET

Zago et al., 2008	1. Numbers Manipulation - Number Maintenance	18	14	Number Operand	Numbers, Math Symbols	Addition	Problem Solving > Baseline	fMRI
Zhou et al., 2007	1. Addition: Large Numbers > Fixation	15	20	Number Operand	Numbers	Addition, Multiplication	Problem Solving > Baseline	fMRI
	2. Addition: Small Numbers > Fixation	15		Number Operand	Numbers	Addition, Multiplication	Problem Solving > Baseline	fMRI
	3. Multiplication: Large Numbers > Fixation	16		Number Operand	Numbers	Addition, Multiplication	Problem Solving > Baseline	fMRI
	4. Multiplication: Small Numbers > Fixation	16		Number Operand	Numbers	Addition, Multiplication	Problem Solving > Baseline	fMRI

b) Verbal Problem Solving Experiments

Publication	Contrast	#Foci	Subjects	Paradigm Classification	Stimulus Type	Task Performed	Contrast Classification	Imaging Modality
Aziz-Zadeh et al., 2009	1. Insight Derived Solutions > Solutions Derived by Searching for Answers	8	10	Insight Problems	Words, Letters	Anagram Problems	Problem Solving Type I > Problem Solving Type II	fMRI

Blackwood et al., 2004	1. Uncertain Decisions > Certain Decisions, Words Task > Balls Task	7	8	Inductive/Probabilistic Reasoning	Words	Probabilistic Reasoning Task	Problem Solving Type I > Problem Solving Type II	fMRI
Canessa et al., 2005	1. Conditional Problems Using Descriptive Words vs. Baseline	18	12	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
	2. Conditional Problems Using Social Exchange Words vs. Baseline	23		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
Christoff et al., 2009	1. Concrete Problems vs. Highly and Moderately Abstract Problems	2	16	Insight Problems	Words, Letters	Anagram Problems	Problem Solving Type I > Problem Solving Type II	fMRI

	2. Moderately Abstract Problems vs. Highly Abstract and Concrete Problems	2		Insight Problems	Words, Letters	Anagram Problems	Problem Solving Type I > Problem Solving Type II	fMRI
	3. Highly Abstract Problems vs. Moderately Abstract and Concrete Problems	5		Insight Problems	Words, Letters	Anagram Problems	Problem Solving Type I > Problem Solving Type II	fMRI
Duncan et al., 2000	1. High g Letter Set Problems vs. Low g Letter Set Problems	3	13	Analogy Problems	Letters	Factor Referenced Cognitive Tests (ETS)	Complex > Simple	PET
Fangmeier et al., 2006	1. Reasoning Processing Phase: Premise 2 - Premise 1	6	12	Deductive Reasoning	Letters	Relational Reasoning Questions	Problem Solving: Phase I > Phase II	fMRI
	2. Reasoning Integration Phase: Premise 2 - Conclusion	9		Deductive Reasoning	Letters	Relational Reasoning Questions	Problem Solving: Phase I > Phase II	fMRI

	3. Reasoning Validation Phase: Conclusion - Premise 2	9		Deductive Reasoning	Letters	Relational Reasoning Questions	Problem Solving: Phase I > Phase II	fMRI
	4. Reasoning - Maintenance Baseline, Integration Phase	4		Deductive Reasoning	Letters	Relational Reasoning Questions	Problem Solving > Baseline	fMRI
	5. Reasoning - Maintenance Baseline, Reasoning Validation Phase	8		Deductive Reasoning	Letters	Relational Reasoning Questions	Problem Solving > Baseline	fMRI
Fangmeier and Knauff, 2009	1. Reasoning Processing Phase: Premise 2 - Premise 1	6	12	Deductive Reasoning	Auditory Presented Letters	Deductive Reasoning Questions	Problem Solving: Phase I > Phase II	fMRI
	2. Reasoning Validation Phase: Premise 2 - Conclusion	9		Deductive Reasoning	Auditory Presented Letters	Deductive Reasoning Questions	Problem Solving: Phase I > Phase II	fMRI

Geake and Hansen, 2005	1. Main Effect: Increasing Analogical Depth in Fluid Analogy Letter Strings	15	12	Analogy Problems	Letter Strings	Fluid Analogy Problems	Complex > Simple	fMRI
Goel et al., 1997	1. Deduction Sentence Problems > Baseline Sentences	3	10	Deductive Reasoning	Sentences	Deductive and Probabilistic/Inductive Reasoning Questions	Problem Solving > Baseline	PET
	2. Induction Sentence Problems > Baseline Sentences	6		Inductive/Probabilistic Reasoning	Sentences	Deductive and Inductive Reasoning Questions	Problem Solving > Baseline	PET
	3. Induction Sentence Problems > Deduction Sentences	2		Inductive/Probabilistic Reasoning	Sentences	Deductive and Inductive Reasoning Questions	Problem Solving Type I > Problem Solving Type II	PET
Goel et al., 1998	1. Syllogism - Baseline	4	12	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	PET
	2. Spatial Relational Questions - Baseline	5		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	PET

	3. Non-spatial Relational Questions - Baseline	3		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	PET
Goel et al., 2000	1. Main Effect of Reasoning: (Content-Based or Content-Free Syllogisms) > Syllogism Baseline	13	11	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
	2. Content-based Syllogism > Syllogism Baseline	7		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
	3. Content-free Syllogism > Syllogism Baseline	11		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
	4. (Content-Rich Reasoning - Syllogism Baseline) and (Content-Free Reasoning - Syllogism Baseline)	10		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving Type I > Problem Solving Type II	fMRI

	5. Content-Free Syllogisms > Content-Rich Syllogisms	10		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving Type I > Problem Solving Type II	fMRI
Goel and Dolan, 2001	1. Main Effect of Reasoning: (Abstract + Concrete Reasoning) - (Abstract + Concrete Baseline)	18	14	Deductive Reasoning	Sentences	Relational Reasoning Questions	Problem Solving > Baseline	fMRI
	2. Concrete Reasoning - Concrete Baseline	12		Deductive Reasoning	Sentences	Relational Reasoning Questions	Problem Solving > Baseline	fMRI
	3. Abstract Reasoning - Abstract Baseline	5		Deductive Reasoning	Sentences	Relational Reasoning Questions	Problem Solving > Baseline	fMRI
	4. (Abstract Reasoning - Abstract Baseline) and (Concrete Reasoning - Concrete Baseline)	21		Deductive Reasoning	Sentences	Relational Reasoning Questions	Problem Solving > Baseline	fMRI

Goel and Dolan, 2004	1. Main Effect of Reasoning: All Reasoning - Baseline Problems	13	16	Both Deductive and Inductive Reasoning	Sentences	Deductive and Probabilistic/Inductive Reasoning Questions	Problem Solving > Baseline	fMRI
	2. Deductive Reasoning - Baseline Problems	12		Deductive Reasoning	Sentences	Deductive and Probabilistic/Inductive Reasoning Questions	Problem Solving > Baseline	fMRI
	3. Inductive Reasoning - Baseline Problems	11		Inductive/Probabilistic Reasoning	Sentences	Deductive and Probabilistic/Inductive Reasoning Questions	Problem Solving > Baseline	fMRI
Goel et al., 2004	1. Unfamiliar Environmental Reasoning - Unfamiliar Environmental Baseline	14	14	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
	2. Familiar Environmental Reasoning - Familiar Environmental Baseline	5		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI

Goel et al., 2009	1. Main Effect of Reasoning: All Reasoning - Baseline	10	17	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
Hao et al., 2013	1. Scientific Problem Solving With Insight Features Highlighted > Scientific Problem Solving Without Insight Features Highlighted	2	17	Insight Problems	Sentences	Scientific Insightful Problem Solving	Problem Solving Type I > Problem Solving Type II	fMRI
Jung-Beeman et al., 2004	1. Insight Solutions > Non-insight Solutions	7	18	Insight Problems	Words	Insight Problem Solving	Problem Solving Type I > Problem Solving Type II	fMRI
Knauff et al., 2002	1. (Relational or Conditional Reasoning) vs. Baseline	18	12	Deductive Reasoning	Auditory Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
Knauff et al., 2003	1. Deductive Reasoning: Visuospatial Relational Words > Rest	4	12	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI

	2. Deductive Reasoning: Visual Words > Rest	6		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
	3. Deductive Reasoning: Spatial Words > Rest	4		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
	4. Deductive Reasoning: Non-Visual, Spatial, or Visuospatial Words > Rest	3		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
	5. Deductive Reasoning: All Word Types > Rest	9		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
Kroger et al., 2008	1. Main Effect of Problem Type: Logic Word Problems - Math Problems	16	12	Deductive Reasoning	Sentences	Logic Word Problems (Mental Venn Diagram Problems)	Problem Solving Type I > Problem Solving Type II	fMRI
Luo and Niki, 2003	1. Insight Achieved in Riddle Problem Solving - Baseline	39	7	Insight Problems	Japanese Characters / Sentences	Riddle Insight Problem Solving	Problem Solving > Baseline	fMRI

Luo et al., 2003	1. Analogical Problem Solving > Semantic Identification of Words	11	10	Analogy Problems	Chinese Characters	Analogy Word Pairs	Problem Solving Type I > Problem Solving Type II	fMRI
Luo et al., 2006	1. Positive Activations in Tight Chunk Decomposition Problems > No Activations in Loose Chunk Decomposition Problems	19	13	Insight Problems	Chinese Characters	Insight Problem Solving (Chinese Character Decomposition)	Complex > Simple	fMRI
Luo et al., 2013	1. New Scientific Insight Problems > Old Scientific Insight Problems, Experiment 1	1	19	Insight Problems	Sentences	Scientific Insightful Problem Solving	Untrained > Trained	fMRI
	2. New Scientific Insight Problems > Old Scientific Insight Problems, Experiment 2	2	17	Insight Problems	Sentences	Scientific Insightful Problem Solving	Untrained > Trained	fMRI

Monti et al., 2007	1. Premise Phase 1 > Fixation: Colored Block or Pseudo-Word Logic Statements, Experiment 1	34	10	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
	2. Colored Block or Pseudo-Word Logic Statements: Complex - Simple Deductions, Experiment 1	31		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Complex > Simple	fMRI
	3. Premise Phase 1 > Fixation: Face or House Logic Statements, Experiment 2	42	12	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
	4. Face or House Logic Statements: Complex - Simple Deductions, Experiment 2	26		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Complex > Simple	fMRI

Monti et al., 2009	1. Logical Problems: Inference - Grammar Identification Baseline	26	15	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
	2. Linguistic Problems: Inference - Grammar Identification Baseline	44		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
Newman et al., 2011	1. Word Problem Solving - Number Problem Solving	10	15	Deductive Reasoning	Sentences	Logic Word Problems	Problem Solving Type I > Problem Solving Type II	fMRI
	2. Easy Word Problem Solving - Fixation	14		Deductive Reasoning	Sentences	Logic Word Problems	Problem Solving > Baseline	fMRI
	3. Hard Word Problem Solving - Fixation	17		Deductive Reasoning	Sentences	Logic Word Problems	Problem Solving > Baseline	fMRI
Noveck et al., 2004	1. Modus Ponens Conditional Problems - Baseline Problems	4	16	Deductive Reasoning	Sentences	Conditional Reasoning Problems	Problem Solving > Baseline	fMRI

	2. Modus Tollens Conditional Problems - Baseline Problems	6		Deductive Reasoning	Sentences	Conditional Reasoning Problems	Problem Solving > Baseline	fMRI
	3. Modus Tollens Conditional Problems - Modus Ponens Conditional Problems	4		Deductive Reasoning	Sentences	Conditional Reasoning Problems	Problem Solving Type I > Problem Solving Type II	fMRI
Osherson et al., 1998	1. Logic Problems vs. Probabilistic Reasoning Problems	8	10	Deductive Reasoning	Sentences	Deductive and Inductive/Probabilistic Reasoning Problems	Problem Solving Type I > Problem Solving Type II	PET
	2. Logic Problems vs. Baseline Non-Meaningful Problems	8		Deductive Reasoning	Sentences	Deductive and Inductive/Probabilistic Reasoning Problems	Problem Solving > Baseline	PET

	3. Probabilistic Reasoning Problems vs. Baseline Non-Meaningful Problems	8		Inductive/Probabilistic Reasoning	Sentences	Deductive and Inductive/Probabilistic Reasoning Problems	Problem Solving > Baseline	PET
Parsons and Osherson, 2001	1. Deduction Reasoning - Probabilistic Reasoning	24	10	Deductive Reasoning	Sentences	Deductive and Probabilistic/Inductive Reasoning Questions	Problem Solving Type I > Problem Solving Type II	PET
Prado and Noveck, 2007	1. Verification Task: 2-Mismatch > 1-Mismatch > 0-Mismatch	10	20	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Complex > Simple	fMRI
	2. Falsification Task: 2-Mismatch > 1-Mismatch > 0-Mismatch	6		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Complex > Simple	fMRI
Qiu et al., 2010	1. Aha Solutions > No-Aha Solutions	19	16	Insight Problems	Chinese Characters	Riddle Insight Problem Solving	Problem Solving Type I > Problem Solving Type II	fMRI

Reverberi et al., 2007	1. Propositional Deductive Inference: (Conditional: Integrable>Non) > (Disjunctive: Integrable>Non)	8	14	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Complex > Simple	fMRI
Reverberi et al., 2010	1. Conditional Problems > Baseline	4	26	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
	2. Syllogistic Problems > Baseline	9		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
Rodriguez-Moreno and Hirsch, 2009	1. Syllogistic Reasoning in Premise 2 Stage > Control Sentences	5	12	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
	2. Syllogistic Reasoning in Conclusion Stage > Control Sentences	9		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
Ruff et al., 2003	1. Reasoning vs. Rest	9	12	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI

	2. Reasoning vs. Maintenance	6		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Problem Solving > Baseline	fMRI
Tian et al., 2011	1. Successful Riddle Problem Solving > Unsuccessful Riddle Problem Solving	7	16	Insight Problems	Chinese Characters	Riddle Insight Problem Solving	Problem Solving Type I > Problem Solving Type II	fMRI
Wagner et al., 2001	1. Strong or Weak Associations: 4 Word Answer Choices > 2 Word Answer Choices	6	14	Analogy Problems	Words	Global Similarity Task (Semantic Association Questions)	Complex > Simple	fMRI
	2. Answer Choice: Weakly Associated to Cue Word > Strongly Associated to Cue Word	22		Analogy Problems	Words	Global Similarity Task (Semantic Association Questions)	Complex > Simple	fMRI

Wendelken et al., 2008	1. (Compare Semantic or Analogy Word Pairs) - (Complete Semantic or Analogy Word Pairs), Primary Analysis	10	20	Analogy Problems	Words	Analogical Reasoning Problems	Problem Solving Type I > Problem Solving Type II	fMRI
	2. All Correctly Answered Semantic or Analogy Questions > Baseline	9		Analogy Problems	Words	Analogical Reasoning Problems	Problem Solving > Baseline	fMRI
	3. Compare Semantic Word Pairs > Baseline	1		Analogy Problems	Words	Analogical Reasoning Problems	Problem Solving > Baseline	fMRI
	4. Compare Analogy Word Pairs > Baseline	1		Analogy Problems	Words	Analogical Reasoning Problems	Problem Solving > Baseline	fMRI

Wu et al., 2013	1. Spatially Tight Character Chunk Decomposition Solutions > Spatially Loose Character Chunk Decomposition Solutions	24	16	Insight Problems	Chinese Characters	Insight Problem Solving (Chinese Character Decomposition)	Complex > Simple	fMRI
	2. Spatially Tight Pseudocharacter Chunk Decomposition Solutions > Spatially Loose Pseudocharacter Chunk Decomposition Solutions	24		Insight Problems	Chinese Characters	Insight Problem Solving (Chinese Character Decomposition)	Complex > Simple	fMRI
	3. Spatially Tight Character Chunk Decomposition Solutions > Spatially Tight Pseudocharacter Chunk Decomposition	9		Insight Problems	Chinese Characters	Insight Problem Solving (Chinese Character Decomposition)	Complex > Simple	fMRI

Zarnhofer et al., 2013	1. Activations: Problems Solving Using a Self-Reported Visualization Strategy	3	36	Deductive Reasoning	Sentences	Arithmetic Word Problems	Problem Solving > Baseline	fMRI
	2. Activations: Problems Solving Using a Self-Reported Verbalization Strategy	6		Deductive Reasoning	Sentences	Arithmetic Word Problems	Problem Solving > Baseline	fMRI
Zhao et al., 2013	1. Insight Solutions > Non-insight Solutions, Early Period of Solution Forming	11	17	Insight Problems	Chinese Characters	Riddle Insight Problem Solving	Problem Solving Type I > Problem Solving Type II	fMRI
	2. Insight Solutions > Non-insight Solutions, Late Period of Solution Forming	15		Insight Problems	Chinese Characters	Riddle Insight Problem Solving	Problem Solving Type I > Problem Solving Type II	fMRI
Zhao et al., 2014	1. Insight Solutions > Rest	12	17	Insight Problems	Chinese Characters	Riddle Insight Problem Solving	Problem Solving > Baseline	fMRI
	2. Insight Solutions > Non-insight Solutions	7		Insight Problems	Chinese Characters	Riddle Insight Problem Solving	Problem Solving Type I > Problem Solving Type II	fMRI

c) Visuospatial Problem Solving Experiments

Publication	*Contrast*	*#Foci*	*Subjects*	*Paradigm Classification*	*Stimulus Type*	*Task Performed*	*Contrast Classification*	*Imaging Modality*
Acuna, 2002	1. Transitive Inference Shape Task > Height Comparison Shape Task	15	17	Visuospatial Relational Reasoning	Pictures	Transitive Inference Task	Problem Solving > Baseline	fMRI
Atherton et al., 2003	1. Identify Best Next Move > Identify Chess Piece	19	8	Additional PS Type	Pictures	Chess Strategy Task	Problem Solving > Baseline	fMRI
Bagga et al., 2014	1. Visual Reasoning > Control, Healthy Controls	6	18	Visuospatial Fluid Reasoning Task	Pictures, Words	Linearly Progressing Shape Task	Problem Solving > Baseline	fMRI
Baker et al., 1996	1. TOL > Baseline	20	6	Tower of London Task	Pictures	Tower of London	Problem Solving > Baseline	PET
Barra et al., 2012	1. Encoding and Shortcut Navigation Mean Activations: (Route + Slanted + Survey Perspectives) > Baseline	20	26	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI

	2. Encoding and Shortcut Navigation: First Person Route > Slanted Perspective	10	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving Type I > Problem Solving Type II	fMRI
	3. Encoding and Shortcut Navigation: Slanted > First Person Route Perspective	3	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving Type I > Problem Solving Type II	fMRI
	4. Encoding and Shortcut Navigation: First Person Route > Ariel Survey Perspective	15	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving Type I > Problem Solving Type II	fMRI
	5. Encoding and Shortcut Navigation: Ariel Survey > First Person Route Perspective	3	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving Type I > Problem Solving Type II	fMRI

	6. All Perspectives: Shortcut Task > Passive Navigation Encoding	28		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving Type I > Problem Solving Type II	fMRI
Beauchamp et al., 2003	1. TOL > One-Move Baseline, Experimental Scan 1	11	12	Tower of London Task	Pictures	Tower of London	Problem Solving > Baseline	PET
	2. TOL > One-Move Baseline, Experimental Scan 10	1		Tower of London Task	Pictures	Tower of London	Problem Solving > Baseline	fMRI
Blackwood et al., 2004	1. Uncertain Decisions > Certain Decisions, Balls Task > Words Task	7	8	Inductive/Probabilistic Reasoning	Pictures	Picture-Based Probabilistic Reasoning Task	Problem Solving Type I > Problem Solving Type II	fMRI
Brown and Stern, 2014	1. Critical Decision Period: Overlapping > Non-overlapping Novel Mazes	27	16	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Complex > Simple	fMRI

	2. Novel Maze Problems: Early Reinforcement Learning Stage	30		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
Campbell et al., 2009	1. Significant Activations: Spatial Navigation Roadblock Planning Task > Baseline	19		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
	2. Significant Activations: Virtual Tower of London Planning Task > Baseline	18		Tower of London Task	Pictures	Tower of London	Problem Solving > Baseline	fMRI
Chen et al., 2003	1. Identify Best Next Go Move > Identify Go Stones With Dots	17	6	Additional PS Type	Pictures	Go Strategy Task	Problem Solving > Baseline	fMRI
	2. Identify Best Next Go Move > Fixate on Empty Go Board	17		Additional PS Type	Pictures	Go Strategy Task	Problem Solving > Baseline	fMRI

Cho et al., 2010	1. Main Effect: Relational Complexity in Analogy Picture Problems	9	17	Visual Analogical Reasoning	Pictures	People Pieces Analogy Task	Complex > Simple	fMRI
Christoff et al., 2001	1. RPM: 2-relational problems vs. 1-relational problems	7	10	Visuospatial Fluid Reasoning Task	Pictures	Raven's Progressive Matrices / Raven's Advanced Progressive Matrices	Complex > Simple	fMRI
Desco et al., 2011	1. RAPM Activations > RAPM Baseline, Controls	12	14	Visuospatial Fluid Reasoning Task	Pictures	Raven's Progressive Matrices / Raven's Advanced Progressive Matrices	Problem Solving > Baseline	fMRI
	2. TOL Activations > TOL Baseline, Controls	21		Tower of London Task	Pictures	Tower of London	Problem Solving > Baseline	fMRI
Duncan et al., 2000	1. Shape Problems: High g Questions vs. Low g Questions	15	13	Visuospatial Fluid Reasoning Task	Pictures	Catell's Culture Fair Test	Complex > Simple	PET
	2. Imbedded Circle Problems: High g Questions vs. Low g Questions	7		Visuospatial Fluid Reasoning Task	Pictures	Catell's Culture Fair Test	Complex > Simple	PET

Ebisch et al., 2012	1. Conjunction of Gf problems: (Induction - Visualization) and (Induction - Spatial Relationships)	5	10	Visuospatial Fluid Reasoning Task	Pictures	Fluid Intelligence Test (FIT; similar to RPM)	Problem Solving Type I > Problem Solving Type II	fMRI
	2. Conjunction of Gf problems: (Visualization - Induction) and (Visualization - Spatial Relationships)	3		Visuospatial Fluid Reasoning Task	Pictures	Fluid Intelligence Test (FIT; similar to RPM)	Problem Solving Type I > Problem Solving Type II	fMRI
Elliott et al., 1997	1. TOL: Solution Planning > Solution Guessing	10	6	Tower of London Task	Pictures	Tower of London	Problem Solving > Baseline	PET
Eslinger et al., 2009	1. Relational Reasoning Pattern Solving > Baseline, Whole Group	17	16	Visuospatial Relational Reasoning	Pictures	Shape-Based Relational Reasoning Task	Problem Solving > Baseline	fMRI
Fincham et al., 2002	1. Goal Processing During Problem Solving > Baseline	13	8	Tower of London Task	Pictures	Tower of London	Problem Solving > Baseline	fMRI

Gagnon et al., 2012	1. Blindfolded Sighted Controls: Maze Navigation > Baseline	5	14	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
Goel and Dolan, 2000	1. Induction Reasoning of Sameness Between Animal Pictures - Perceptual Baseline	12	10	Inductive/Probabilistic Reasoning	Pictures	Animal Picture Rule Task	Problem Solving > Baseline	fMRI
	2. Rule Application of Sameness Between Animal Pictures - Perceptual Baseline	12		Inductive/Probabilistic Reasoning	Pictures	Animal Picture Rule Task	Problem Solving > Baseline	fMRI
Grön et al., 2000	1. Whole Group: Maze Problem Navigation > Baseline	18	24	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
Hampshire et al., 2011	1. Visual Reasoning > Baseline, Simultaneous Picture Presentation	11	16	Visuospatial Fluid Reasoning Task	Pictures	Nonverbal Reasoning Problems	Problem Solving > Baseline	fMRI

	2. Main Effect: Visual Rule Complexity, Simultaneous Picture Presentation	9	Visuospatial Fluid Reasoning Task	Pictures	Nonverbal Reasoning Problems	Complex > Simple	fMRI
	3. Main Effect: Analogical Distance, Simultaneous Picture Presentation	6	Visuospatial Fluid Reasoning Task	Pictures	Nonverbal Reasoning Problems	Complex > Simple	fMRI
	4. Visual Reasoning Rule Complexity - Analogical Distance, Simultaneous Picture Presentation	9	Visuospatial Fluid Reasoning Task	Pictures	Nonverbal Reasoning Problems	Complex > Simple	fMRI
	5. Main Effect: Rule Complexity, Successive Picture Presentation	5	Visuospatial Fluid Reasoning Task	Pictures	Nonverbal Reasoning Problems	Complex > Simple	fMRI

	6. Main Effect: Analogical Distance, Successive Picture Presentation	5		Visuospatial Fluid Reasoning Task	Pictures	Nonverbal Reasoning Problems	Complex > Simple	fMRI
Hartley et al., 2003	1. Wayfinding > Trail Following	8	16	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
	2. Wayfinding > Route Following	12	16	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Untrained > Trained	fMRI
Heckers et al., 2004	1. Main Effect: Transitive Inference	13	16	Visuospatial Relational Reasoning	Pictures	Transitive Inference Picture Task	Problem Solving > Baseline	fMRI
Hirshhorn et al., 2012	1. Session 1 Conjunction: (Blocked-Route Problem Solving > Baseline) and (Distance and Proximity Judgment > Baseline)	15	13	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI

Houdé et al., 2000	1. Relational Deduction After Logic Training > Relational Deduction Before Logic Training	19	8	Visuospatial Relational Reasoning	Pictures	Shape Relational Deduction Task	Untrained > Trained	PET
Iaria et al., 2003	1. Maze Task > Visuomotor Control Task	17	14	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
Iaria et al., 2008	1. Unexpected Renavigation: Blocked Path with Solution > Learned Path with Trivial Detour	7	10	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Untrained > Trained	fMRI
	2. Unexpected Renavigation: Blocked Path without Solution > Learned Path with Trivial Detour	3		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Untrained > Trained	fMRI

	3. Unexpected Renavigation: Blocked Path with Solution > Learned Path with Trivial Perceptual Change	11		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Untrained > Trained	fMRI
	4. Unexpected Renavigation: Blocked Path without Solution > Learned Path with Trivial Perceptual Change	2		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Untrained > Trained	fMRI
Kalbfleisch et al., 2007	1. NNAT Hard > NNAT Easy	18	14	Visuospatial Fluid Reasoning Task	Pictures	Naglieri Nonverbal Ability Test (NNAT)	Complex > Simple	fMRI
Kroger et al., 2002	1. RPM: Complexity levels 3-4 - Distractor levels 3-4	8	8	Visuospatial Fluid Reasoning Task	Pictures	Raven's Progressive Matrices / Raven's Advanced Progressive Matrices	Problem Solving > Baseline	fMRI

Lu et al., 2010	1. Triangle Number Problem: Calculation Via Location-Based Rule Induction > Simple Calculation	15	20	Inductive/Probabilistic Reasoning	Pictures, Numbers	Spatially Dependent Calculation Task	Problem Solving Type I > Problem Solving Type II	fMRI
Marsh et al., 2010	1. Novel Maze Navigation During Spatial Learning Phase > Trail Following	9	25	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
Masunaga et al., 2008	1. Catell's Culture Fair Test > Control Image Task	16	18	Visuospatial Fluid Reasoning Task	Pictures	Catell's Culture Fair Test	Problem Solving > Baseline	fMRI
Melrose et al., 2007	1. Problem Solving Using Reasoning > Problem Using With Matching	14	19	Visuospatial Fluid Reasoning Task	Pictures	Linearly Progressing Shapes Task	Problem Solving > Baseline	fMRI
	2. Problem Solving Using Reasoning > Reasoning Control	33		Visuospatial Fluid Reasoning Task	Pictures	Linearly Progressing Shapes Task	Problem Solving > Baseline	fMRI

Perfetti et al., 2009	1. RPM: Problem Solving > Baseline, Whole Group	11	18	Visuospatial Fluid Reasoning Task	Pictures	Raven's Progressive Matrices / Raven's Advanced Progressive Matrices	Problem Solving > Baseline	fMRI
Preusse et al., 2010	1. Time Point 1: Main Effect of Task Difficulty	4	22	Visual Analogical Reasoning	Pictures	Geometric Analogical Reasoning Task (like RPM)	Complex > Simple	fMRI
	2. Time Point 2: Main Effect of Task Difficulty	4	17	Visual Analogical Reasoning	Pictures	Geometric Analogical Reasoning Task (like RPM)	Complex > Simple	fMRI
Rauchs et al., 2008	1. Navigate to Target Location : Blocked Route > Learned Route	28	16	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Untrained > Trained	fMRI
	2. Navigate to Target Location : Blocked Route > Learned Route Devoid of Familiar Landmarks	14		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving Type I > Problem Solving Type II	fMRI

	3. Navigate to Target Location within Blocked Route Condition: Detour > Well-Known Part of Route	15		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Untrained > Trained	fMRI
Sherrill et al., 2013	1. Maze Navigation Phase: First Person Perspective > Previously Encoded Ariel Map Perspective	14	18	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
	2. Maze Navigation Phase: Third Person Perspective > Previously Encoded Ariel Map Perspective	14		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI

	3. Maze Navigation Phase: First Person Perspective > Third Person Perspective	8		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving Type I > Problem Solving Type II	fMRI
	4. Maze Navigation Phase: Third Person Perspective > First Person Perspective	10		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving Type I > Problem Solving Type II	fMRI
Siemerkus et al., 2012	1. Novel Maze Navigation in Healthy Controls: Decide Which Direction at Intersection > Baseline	25	16	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
Unterrainer et al., 2005	1. Performance Related Activations During TOL Planning phase	6	20	Tower of London Task	Pictures	Tower of London	Problem Solving > Baseline	fMRI
van den Heuvel et al., 2005	1. TOL Planning Phase > Baseline, Normals	19	22	Tower of London Task	Pictures	Tower of London	Problem Solving > Baseline	fMRI

	2. Increased Activation Correlating with Task Difficulty, Normals	21		Tower of London Task	Pictures	Tower of London	Complex > Simple	fMRI
Van Horn et al., 1998	1. Naïve Maze Navigation > Baseline	15	15	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
	2. Practiced Maze Navigation > Baseline	7		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
	3. Maze Navigation: Naïve > Practiced	22		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Untrained > Trained	fMRI
Wagner et al., 2006	1. TOL Planning Phase > Ball Counting	10	7	Tower of London Task	Pictures	Tower of London	Problem Solving > Baseline	fMRI
	2. TOL Planning Phase > Indicate Number of Moved Balls	11		Tower of London Task	Pictures	Tower of London	Problem Solving > Baseline	fMRI

Watson and Chatterjee, 2012	1. Shape/Color Analogy Questions > Shape/Color Matching Questions	3	23	Visual Analogical Reasoning	Pictures	Color and Shape Analogy Task	Problem Solving > Baseline	fMRI
Wendelken and Bunge, 2010	1. Transitive Inference Problems > Direct Comparison Problems	3	16	Visuospatial Relational Reasoning	Pictures	Picture-Based Transitive Inference Task	Problem Solving Type I > Problem Solving Type II	fMRI
	2. Specific Relational Encoding Problems > General Relation Problems	8		Visuospatial Relational Reasoning	Pictures	Picture-Based Transitive Inference Task	Problem Solving Type I > Problem Solving Type II	fMRI
Weniger et al., 2010	1. Maze Navigation: Decide Which Direction at Intersection > Baseline	17	19	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI

Weniger et al., 2013	1. Novel Maze Navigation in Healthy Controls: Decide Which Direction at Intersection > Baseline	26	14	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
Wharton et al., 2000	1. Analogy Shape Questions - Literal Shape Matching	8	12	Visual Analogical Reasoning	Pictures	Patterned Shape Analogy Task	Problem Solving > Baseline	PET
Xu et al., 2010	1. Navigate to Target Location: All Landmarks Removed > Line Following	18	20	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
	2. Navigate to Target Location: Blocked Path > Line Following	14		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
	3. Navigate to Target Location: Blocked Path > Learned Route	7		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI

	4. Navigate to Target Location : All Landmarks Removed > Blocked Path	1		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
	5. Navigate to Target Location : Blocked Path > All Landmarks Removed	6		Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI
Yoshida and Ishii, 2006	1. Maze Navigation: Goal-Search > Visuomotor Control	8	13	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Problem Solving > Baseline	fMRI

d) Problem Demand Experiments

Publication	*Contrast*	*#Foci*	*Subjects*	*Paradigm Classification*	*Stimulus Type*	*Task Performed*	*Representation Classification*	*Imaging Modality*
Brown and Stern, 2014	1. Critical Decision Period: Overlapping > Non-overlapping Novel Mazes	27	16	Spatial Navigation Problem Solving	Pictures	Maze Navigation Task	Visuospatial	fMRI

Christoff et al., 2001	1. RPM: 2-relational problems vs. 1-relational problems	7	10	Visuospatial Fluid Reasoning Task	Pictures	Raven's Progressive Matrices / Raven's Advanced Progressive Matrices	Visuospatial	fMRI
Cho et al., 2010	1. Main Effect: Relational Complexity in Analogy Picture Problems	9	17	Visual Analogical Reasoning	Pictures	People Pieces Analogy Task	Visuospatial	fMRI
Duncan et al., 2000	1. Shape Problems: High g Questions vs. Low g Questions	15	13	Visuospatial Fluid Reasoning Task	Pictures	Catell's Culture Fair Test	Visuospatial	PET
	2. Imbedded Circle Problems: High g Questions vs. Low g Questions	7		Visuospatial Fluid Reasoning Task	Pictures	Catell's Culture Fair Test	Visuospatial	fMRI
	3. High g Letter Set Problems vs. Low g Letter Set Problems	3		Analogy Problems	Letters	Factor Referenced Cognitive Tests (ETS)	Verbal	fMRI

Fehr et al., 2007	1. Complex Addition > Simple Addition	17	11	Number Operand	Numbers, Math Symbols	Addition, Subtraction, Multiplication, Division	Mathematical	fMRI
	2. Complex Subtraction > Simple Subtraction	18		Number Operand	Numbers, Math Symbols	Addition, Subtraction, Multiplication, Division	Mathematical	fMRI
	3. Complex Multiplication > Simple Multiplication	9		Number Operand	Numbers, Math Symbols	Addition, Subtraction, Multiplication, Division	Mathematical	fMRI
	4. Complex Division > Simple Division	15		Number Operand	Numbers, Math Symbols	Addition, Subtraction, Multiplication, Division	Mathematical	fMRI
Geake and Hansen, 2005	1. Main Effect: Increasing Analogical Depth in Fluid Analogy Letter Strings	15	12	Analogy Problems	Letter Strings	Fluid Analogy Problems	Verbal	PET
Grabner et al., 2007	1. Multi-Digit Multiplication > Single-Digit Multiplication	15	12	Number Operand	Numbers, Equations	Multiplication Verification	Mathematical	fMRI
	2. Procedural Calculation > Answer Retrieval	9	28	Number Operand	Numbers, Equations	Addition, Subtraction, Multiplication, Division	Mathematical	fMRI

Hampshire et al., 2011	1. Main Effect: Visual Rule Complexity, Simultaneous Picture Presentation	9	16	Nonverbal Reasoning Problems	Pictures	Nonverbal Reasoning Problems	Visuospatial	fMRI
	2. Main Effect: Analogical Distance, Simultaneous Picture Presentation	6		Nonverbal Reasoning Problems	Pictures	Nonverbal Reasoning Problems	Visuospatial	fMRI
	3. Visual Reasoning Rule Complexity - Analogical Distance, Simultaneous Picture Presentation	9		Nonverbal Reasoning Problems	Pictures	Nonverbal Reasoning Problems	Visuospatial	fMRI
	4. Main Effect: Rule Complexity, Successive Picture Presentation	5		Nonverbal Reasoning Problems	Pictures	Nonverbal Reasoning Problems	Visuospatial	fMRI

	5. Main Effect: Analogical Distance, Successive Picture Presentation	5		Nonverbal Reasoning Problems	Pictures	Nonverbal Reasoning Problems	Visuospatial	fMRI
Kalbfleisch et al., 2007	1. NNAT Hard > NNAT Easy	18	14	Visuospatial Fluid Reasoning Task	Pictures	Naglieri Nonverbal Ability Test (NNAT)	Visuospatial	fMRI
Kong et al., 2005	1. Main Effect of Complexity: Carrying/Borrowing vs. No Carrying/Borrowing	4	16	Number Operand	Numbers, Equations	Addition, Subtraction	Mathematical	fMRI
Lazeron et al., 2003	1. High Speed PVSAT vs. Low Speed PVSAT	10	9	PASAT / PVSAT	Numbers	Addition	Mathematical	fMRI
Luo et al., 2006	1. Positive Activations in Tight Chunk Decomposition Problems > No Activations in Loose Chunk Decomposition Problems	19	13	Insight Problems	Chinese Characters	Insight Problem Solving (Chinese Character Decomposition)	Verbal	fMRI

Monti et al., 2007	1. Colored Block or Pseudo-Word Logic Statements: Complex - Simple Deductions, Experiment 1	31	10	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Verbal	fMRI
	2. Face or House Logic Statements: Complex - Simple Deductions, Experiment 2	26		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Verbal	PET
Montojo and Courtney, 2008	1. Calculation with NMBR, RULE, BOTH switching > Calculation with HOLD for Number and Rule	6	16	Number Operand	Numbers	Addition, Subtraction	Mathematical	PET
	2. Main Effect: Calculation (NMBR Switching, RULE Switching, Switching BOTH Number and Rule)	7		Number Operand	Numbers	Addition, Subtraction	Mathematical	fMRI

Prado and Noveck, 2007	1. Verification Task: 2-Mismatch > 1-Mismatch > 0-Mismatch	10	20	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Verbal	fMRI
	2. Falsification Task: 2-Mismatch > 1-Mismatch > 0-Mismatch	6		Deductive Reasoning	Sentences	Deductive Reasoning Questions	Verbal	PET
Preusse et al., 2010	1. Time Point 1: Main Effect of Task Difficulty	4	22	Visual Analogical Reasoning	Pictures	Geometric Analogical Reasoning Task (like RMP)	Visuospatial	fMRI
	2. Time Point 2: Main Effect of Task Difficulty	4	17	Visual Analogical Reasoning	Pictures	Geometric Analogical Reasoning Task (like RMP)	Visuospatial	fMRI
Reverberi et al., 2007	1. Propositional Inference Conjunction: (Conditional: Integrable>Non) > (Disjunctive: Integrable>Non)	8	14	Deductive Reasoning	Sentences	Deductive Reasoning Questions	Verbal	fMRI

van den Heuvel et al., 2005	1. Increased Activation Correlating with Task Difficulty, Normals	21	22	Tower of London Task	Pictures	Tower of London	Visuospatial	fMRI
Wagner et al., 2001	1. Strong or Weak Associations: 4 Word Answer Choices > 2 Word Answer Choices	6	14	Analogy Problems	Words	Global Similarity Task (Semantic Association Questions)	Verbal	fMRI
	2. Answer Choice: Weakly Associated to Cue Word > Strongly Associated to Cue Word	22		Analogy Problems	Words	Global Similarity Task (Semantic Association Questions)	Verbal	fMRI
Wood et al., 2008	1. Large Number Bisection Range > Small Number Bisection Range	18	17	Additional PS Type	Numbers	Number Bisection Task (NBT)	Mathematical	fMRI
	2. Number Decade Crossing > No Number Decade Crossing	17		Additional PS Type	Numbers	Number Bisection Task (NBT)	Mathematical	fMRI

	3. Large Number Problem Size > Small Number Problem Size	6		Additional PS Type	Numbers	Number Bisection Task (NBT)	Mathematical	fMRI
	4. Large Number Distance to Mean > Small Number Distance to Mean	5		Additional PS Type	Numbers	Number Bisection Task (NBT)	Mathematical	fMRI
Wu et al., 2013	1. Spatially Tight Character Chunk Decomposition Solutions > Spatially Loose Character Chunk Decomposition Solutions	24	16	Insight Problems	Chinese Characters	Insight Problem Solving (Chinese Character Decomposition)	Verbal	fMRI
	2. Spatially Tight Pseudocharacter Chunk Decomposition Solutions > Spatially Loose Pseudocharacter Chunk Decomposition Solutions	24		Insight Problems	Chinese Characters	Insight Problem Solving (Chinese Character Decomposition)	Verbal	fMRI

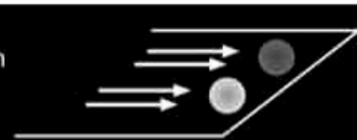
	3. Spatially Tight Character Chunk Decomposition Solutions > Spatially Tight Pseudocharacter Chunk Decomposition	9	Insight Problems	Chinese Characters	Insight Problem Solving (Chinese Character Decomposition)	Verbal	fMRI

A.2 Post-scan FCI Questionnaire

Figure A.1 Post-scan FCI Reasoning Questionnaire. All participants completed a reasoning and strategy questionnaire immediately after exiting the MRI scanner. The questionnaire asked students to select how they arrived at the answers they provided to the nine in-scanner MRI questions while in the scanner. Their answers were used in to perform the parametric modulation analyses of Chapter 4

For each question below please indicate: the answer you chose, how you would characterize your general approach to solving the problem, and your overall confidence level.

Two balls are the same size but one is twice as heavy. They roll off a horizontal table with the same constant speed at the same time.



How far away from the table's base do they hit the floor?

(A) Both balls hit at the same horizontal distance away from the table's base.

(B) The heavier ball hits at half the horizontal distance than the lighter ball.

(C) The lighter ball hits at half the horizontal distance than the heavier ball.

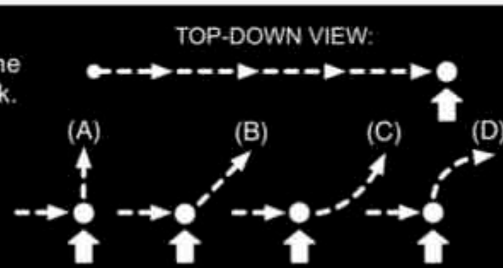
(D) The heavier ball hits much closer to the table's base than the lighter one.

WHAT ANSWER DID YOU CHOOSE? A B C D	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I used knowledge and reasoning to arrive at my answer.					
I relied on a "gut feeling" to arrive at my answer.					
I am confident that the answer I provided is correct.					

Briefly describe why the answer you chose makes the most sense.

A puck slides across ice with a constant speed. After a while, the puck gets a quick horizontal kick.

Which path would the puck take after the kick?



(A) The puck would move along path A.

(B) The puck would move along path B.

(C) The puck would move along path C.

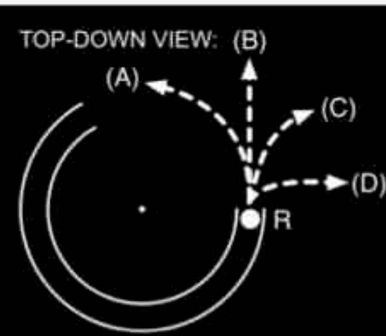
(D) The puck would move along path D.

WHAT ANSWER DID YOU CHOOSE? A B C D	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I used knowledge and reasoning to arrive at my answer.					
I relied on a "gut feeling" to arrive at my answer.					
I am confident that the answer I provided is correct.					

Briefly describe why the answer you chose makes the most sense.

A ball is shot at high speed through a frictionless semicircular channel. The ball exits the channel at point R.

Which path would the ball take after exiting?



(A) The ball would move along path A.

(B) The ball would move along path B.

(C) The ball would move along path C.

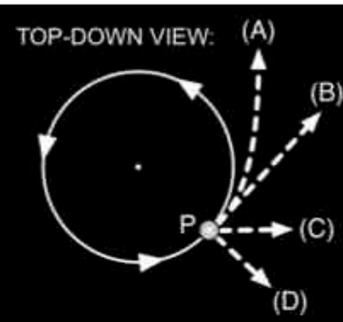
(D) The ball would move along path D.

WHAT ANSWER DID YOU CHOOSE? A B C D	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I used knowledge and reasoning to arrive at my answer.					
I relied on a "gut feeling" to arrive at my answer.					
I am confident that the answer I provided is correct.					

Briefly describe why the answer you chose makes the most sense.

A ball is attached to a string and swung in a horizontal circular path. At point P the string suddenly breaks near the ball.

Which path would the ball take after the string breaks?



(A) The ball would move along path A.

(B) The ball would move along path B.

(C) The ball would move along path C.

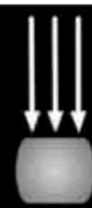
(D) The ball would move along path D.

WHAT ANSWER DID YOU CHOOSE? A B C D	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I used knowledge and reasoning to arrive at my answer.					
I relied on a "gut feeling" to arrive at my answer.					
I am confident that the answer I provided is correct.					

Briefly describe why the answer you chose makes the most sense.

A stone is dropped from the roof
of a single story building and
falls to the surface of the earth.

What happens to the stone as it falls?
The stone...



(A) Quickly reaches a maximum speed and then falls at a constant rate.

(B) Speeds up as it falls because gravity gets stronger closer to the earth.

(C) Speeds up because of a nearly constant force of gravity acting on it.

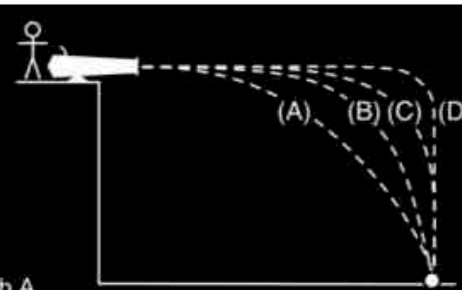
(D) Falls because of the force of gravity and a downward force from the air.

WHAT ANSWER DID YOU CHOOSE? A B C D	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I used knowledge and reasoning to arrive at my answer.					
I relied on a "gut feeling" to arrive at my answer.					
I am confident that the answer I provided is correct.					

Briefly describe why the answer you chose makes the most sense.

A ball is fired by a horizontal cannon from the top of a cliff. Eventually it hits the ground.

Which path would the ball take as it moves?



(A) The ball would move along path A.

(B) The ball would move along path B.

(C) The ball would move along path C.

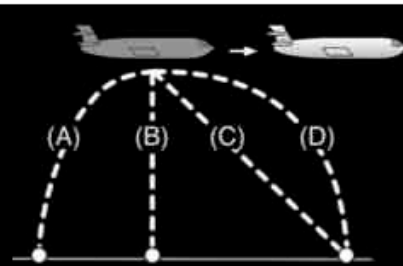
(D) The ball would move along path D.

WHAT ANSWER DID YOU CHOOSE? A B C D	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I used knowledge and reasoning to arrive at my answer.					
I relied on a "gut feeling" to arrive at my answer.					
I am confident that the answer I provided is correct.					

Briefly describe why the answer you chose makes the most sense.

A heavy ball falls from an airplane as it flies along in a horizontal direction. Air resistance is small and can be ignored.

Which path would the ball take after leaving the airplane?



(A) The ball would move along path A.

(B) The ball would move along path B.

(C) The ball would move along path C.

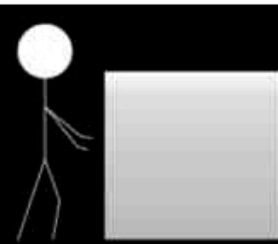
(D) The ball would move along path D.

WHAT ANSWER DID YOU CHOOSE? A B C D	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I used knowledge and reasoning to arrive at my answer.					
I relied on a "gut feeling" to arrive at my answer.					
I am confident that the answer I provided is correct.					

Briefly describe why the answer you chose makes the most sense.

A woman pushes a box with constant horizontal force so it moves with constant speed across a floor. Suddenly, the woman lets go of the box.

How does the box move after her force has been removed?



(A) The box immediately stops.

(B) It continues at a constant speed for a while and then slows to a stop.

(C) The box immediately starts slowing to a stop.

(D) The box continues moving across the floor at a constant speed.

WHAT ANSWER DID YOU CHOOSE? A B C D	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I used knowledge and reasoning to arrive at my answer.					
I relied on a "gut feeling" to arrive at my answer.					
I am confident that the answer I provided is correct.					

Briefly describe why the answer you chose makes the most sense.

An office chair is at rest on the floor. No one is sitting on the chair and it remains still.

What forces are acting on the chair? The chair feels...

(A) A downward force from gravity only.

(B) A downward force from gravity and an upward force from the floor.

(C) Net forces down from gravity, up from the floor, and down from the air.

(D) The chair is at rest so it experience no forces at all.

WHAT ANSWER DID YOU CHOOSE? A B C D	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
I used knowledge and reasoning to arrive at my answer.					
I relied on a "gut feeling" to arrive at my answer.					
I am confident that the answer I provided is correct.					

Briefly describe why the answer you chose makes the most sense.

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SELECTED PUBLICATIONS AND PRESENTATIONS

Bartley JE, Riedel MC, Salo T, Boeving ER, Bottenhorn KL, Bravo EI, Odean R, Nazareth A, Laird RW, Sutherland MT, Pruden SM, Brewe E, Laird AR. Brain networks supporting physics cognition and knowledge organization in undergraduate students. Nature Science of Learning, (under review)

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