

Computational Thinking: Changes to the Human Connectome Associated with Learning to Program

Completed Research Paper

INTRODUCTION

Computational thinking ([Guzdial 2008](#); [Wing 2006](#); [Wing 2008](#)) means solving problems using a logical, often mathematical, foundation. One important type of computational thinking involves being able to observe a problem in the world and then formulate a plan of action that can be carried out by a computer. Computational thinking is what computing professionals (MIS personnel, computer scientists) do when they analyze and design systems.

However, computational thinking is important not only for designing information systems. In fact, it is difficult to overstate the importance of computational thinking in the modern world. As the Center for Computational Thinking at Carnegie Mellon states, “*Simply put, it is nearly impossible to do scholarly research in any scientific or engineering discipline without an ability to think computationally. The impact of computing extends far beyond science, however, affecting all aspects of our lives. To flourish in today’s world, everyone needs computational thinking*” ([Center for Computational Thinking Website 2014](#)). With the continuing decentralization of decision making to individuals (e.g., healthcare, retirement investing, travel planning), the need for computational thinking in all citizens is increasing rapidly and is likely to continue to grow significantly in the future.

Unfortunately, it is not clear what, if anything, separates computational thinking from other types of thinking. Is it simply a skill like riding a bicycle or reading music that can be learned, or is it something special that requires a specific and unique brain structure to accomplish? This is an important question because if computational thinking is a special sort of skill, but one that everyone needs to navigate and succeed in today’s world, then it is important to develop this skill in many more people.

In this paper we use the magnetic resonance imaging technique called diffusion tensor imaging (DTI) to investigate whether and how teaching computational thinking—programming specifically—changes the brain structure of learners. We compare changes in the brain structure of students taking their first programming course to similar students who are not taking such a course. We explore the question of whether computational thinking is simply a change in intelligence¹, which can be improved through any sort of learning, or whether it involves specific structural changes in the brains of the learners.

We contribute to the IS literature by demonstrating the computational thinking skills acquired during the learning of computer programming. Of special note are our findings concerning conflict resolution and feedback during computational thinking. These results are important for both theory and practice. We also are the first to utilize the DTI method in the mainstream IS domain, thus contributing methodologically to the IS field.

The remainder of the paper is organized as follows. We provide general background material on the human connectome and then provide theory underlying neuroplasticity and the learning of programming. We then develop hypotheses based on this theory. We then test the hypotheses using the neuroscience DTI method and report the results of our findings. We conclude with a summary of the results and implications for theory and practice.

¹ Intelligence is a complex phenomenon in the brain and has been the subject of much discussion in the psychology, philosophy, and neuroscience literatures (see, e.g., Jung et al. 2007). Numerous different types of intelligence have been proposed. “General intelligence” (g) has been convincingly demonstrated to consist of two distinct psychometric components: “fluid intelligence” (gF) and “crystallized intelligence” (gC) (Lee et al. 2006). Fluid intelligence is reasoning and problem-solving skill independent of prior experience and knowledge, which is arguably characteristic of most college courses (Gebauer et al. 2007). Thus, when we refer to “intelligence” in the current article, unless otherwise specified, we are referring to “fluid intelligence” (gF).

BACKGROUND

The term “connectome” has recently entered the awareness of researchers with the Obama administration’s announcement of plans to fund the Brain Activity Map, which has the goal of mapping the human brain in the same way that the Human Genome project mapped the human genome. Using the root from genome, the term connectome refers to the set of all connections in the human brain. Roughly speaking, the brain is made up many clusters of tissue, each of which handles a very specialized task. To accomplish anything useful, these areas must communicate with each other. The connectome is the set of connections that allow that communication.

Physically, the clusters through which people process tasks are gray matter, so named because the tissue is actually gray. Gray matter primarily covers the outside of the brain in a shell called the cortex. Underneath the gray matter is white matter. White matter acquires its color from a fat called myelin that serves to insulate the fibers connecting different regions of gray matter. At the simplest level, white matter can be thought of as wires that connect the gray matter; gray matter can be thought of as processors.

In this research we explore two types of connectivity associated with intelligence or mental performance in the context of computational thinking, specifically learning a programming language. These are frontal to parietal lobe connectivity and connectivity between the frontal cortex and the cingulate cortex ([Jung et al. 2007](#); [Prescott et al. 2010](#)). We discuss the locations and functions of these brain areas in our theory and hypothesis development section below. To our knowledge, no work to date has documented changes in actual brain structure associated with the learning of a programming language.

THEORY

Neuroplasticity refers to structural changes in the brain associated with environmental demands, such as learning, and the ability of the brain to re-wire itself. A decade ago, the dominant belief was that learning was associated only with functional changes in the brain, and not with gross structural changes. However, more recent studies have begun to overturn this view and document structural changes in a variety of domains. One of the first papers to hint at structural changes studied London taxi drivers ([Maguire et al. 2000](#)). The authors found that taxi drivers had a larger posterior hippocampal region (memory region) than control subjects, and that the size of this region correlated with the time spent as a taxi driver. One of the first studies showing gray matter changes within individuals examined the effect of learning how to juggle ([Draganski et al. 2004](#)). The researchers found changes in gray matter in the occipital-temporal cortex in an area known to be sensitive to motion after three months of juggling training. A follow-up study found changes in gray matter due to juggling after only one week of training ([Driemeyer et al. 2008](#)). Meditation has also been shown to change cortical thickness in as little as one week, although that week consisted of 10 hours of meditation per day ([Lazar et al. 2005](#)).

Changes in white matter structure have only been documented more recently. Perhaps the first paper to do so was also in the domain of juggling. Scholz et al. found increases in fractional anisotropy (a measure of how consistently a series of neurons in a voxel (defined below) move in the same direction) as a result of learning to juggle ([Scholz et al. 2009](#)). After learning how to juggle and training for six weeks, subjects showed increased fractional anisotropy in the inter parietal sulcus, an area that connects visual and motor regions of the brains and is believed to facilitate coordination between motor skills and visual perception—exactly what a person needs to juggle.

Meditation has also been shown to have structural effects on white matter ([Tang et al. 2010](#)). After practicing a meditation technique called integrative body-mind training for only eleven hours, subjects showed increases in the fractional anisotropy of the anterior cingulate cortex. This area of the brain coordinates a variety of activities, and activation deficits of the anterior cingulate have been implicated in depression, attention deficit disorder, and dementia.

White matter changes as measured via tractography (a method for creating maps of white matter tracts) have been documented in a study by [Schlaug et al. \(2009\)](#) in response to speech therapy following strokes. Following a stroke, six patients were scanned and then given a type of speech therapy called Melodic Intonation Therapy. Following 12 or more weeks of therapy subjects were rescanned and tractography was applied to the two scans. Patients showed a significant increase in the number of fibers as measured

by tractography in the right arcuate fasciculus, a white matter track that connects regions responsible for auditory feedback, planning, and executing motor actions.

These studies illustrate the concept of neuroplasticity of the brain. As the brain is used for specific tasks the gray matter underlying the functional components of the task rearranges itself. Moreover, the white matter that connects relevant gray matter regions rearranges itself to facilitate effective communication among the appropriate gray matter regions.

A primary goal of MIS education is to teach computational thinking. As students work their way through a program of study, they can be expected to improve at computational thinking. Ultimately, these changes should show themselves in the brain structure of students. Just as training in a sport will change the musculature of the athlete, training in a mental discipline will result in changes in the brain (see Carr 2010). Thus, if we observe the brains of students before and after training, then we should be able to observe the structural changes associated with computational thinking.

There are two ways that learning to program could potentially impact brain structures. First, learning to program may be just like learning anything else and be measurable as fluid intelligence (gF). Second, learning to program may teach a special way of thinking, i.e., it may have some unique properties not common to general learning.

The first theory we examine is based on the premise that education in general increases intelligence. There is some dispute about whether this is true (Ceci et al. 1997; Herrnstein et al. 2010; Winship et al. 1997), but it is a reasonable starting premise. If it is true, then we should be able to detect structural changes in connectivity associated with intelligence. One theory suggests that integration between the parietal and frontal lobes accounts for a great deal of intelligence (Jung and Haier 2007). After reviewing 37 neuroimaging studies—both functional and structural—Jung and Haier (2007) proposed the Parietal-Frontal Integration Theory (P-FIT). The crux of this theory is that neuroimaging studies usually find the frontal and parietal regions to be important in explaining intelligence. This occurs across many different measures of intelligence, and across many different imaging modalities. Roughly speaking, the parietal lobe is responsible for constructing the meaning of the things we observe in the world and the frontal lobe is responsible for testing the different reactions to the things we observe. For example, S-H-A-R-K is just a combination of letters until it arrives at the parietal lobe, at which time it becomes a word with associated connotations. The parietal lobe then sends this idea to the frontal lobes, which contemplate different reactions, such as approach or avoid. This is of course a simplified explanation, but it provides a basic understanding of the importance of the parietal and frontal areas.

The next important feature of P-FIT theory is the notion of “integration.” The ability to be intelligent requires interaction between meaning and potential results. It is not sufficient to hold deep meaning nor is it sufficient to generate many potential results; it is necessary to attach the right result to the right meaning. To accomplish this requires communication between the parietal and frontal regions, and to communicate requires white matter tracts connecting the two regions.

If programming training increases intelligence in a general way, and if intelligence depends on white matter connectivity between the frontal and parietal regions, then we should observe an increase in the connections between the frontal and parietal regions in response to a student learning to program. Therefore, our first hypothesis is:

General Intelligence Hypothesis: Subjects will show an increase in Parietal-Frontal connectivity after taking a course in programming.

Another possibility is that computational thinking may not be related directly to general intelligence. In other words, computational thinking may require something special—something more than just general intelligence. One promising place to start the search for a special feature is in the literature on mathematical ability. While computational thinking is not a well-studied area, mathematical ability has been studied extensively, and research in that area can offer insights. Computational thinking and mathematical ability are both about solving problems within a finite set of rules.

Mathematical ability has been found to be linked to both the prefrontal regions of the brain and the anterior cingulate cortex (ACC) (Desco et al. 2011; O'Boyle 2008; O'Boyle et al. 2005). The prefrontal regions are above the eye sockets and are associated with executive control. These are the areas of the brain that perform what most people consider “thinking.”

The ACC is deeper in the brain and is associated with on-line monitoring and conflict control. It has been theorized that the ACC is part of a network that works to promote strategies that reduce conflict (Botvinick 2007; Botvinick et al. 2004; Kerns et al. 2004). When a person undertakes an action and the result is problematic, the ACC activates and tries to allocate resources to other behavioral strategies that reduce conflict. This sort of activity is important for intelligent thinking because intelligence is in part about engaging in behavior that is appropriate to the situation.² Neural mechanisms that help correct problematic behavior promote intelligent behavior.

With respect to computational thinking, coordination between the ACC and prefrontal cortex should be particularly important. The prefrontal cortex can develop and/or propose an algorithm and the ACC can evaluate whether it results in conflict. A large part of MIS professionals' work is to resolve conflicts between different computational systems, whether entire information systems or just single lines of code. One of the most basic questions in computational thinking is, “If I do X will there be a conflict?” This is exactly the sort of question that requires communication between the prefrontal cortex and the ACC. Therefore we hypothesize:

Conflict Minimizing Hypothesis: Subjects will show an increase in prefrontal cortex to anterior cingulate cortex connectivity after taking a course in programming.

For students learning programming, conflict resolution and avoidance are important for computational thinking. When a student learns to program he is constantly and immediately presented with conflicts, ranging from error messages to unexpected behavior. This conflict feedback is offered relentlessly and nearly constantly by the programming framework. In fact, it is not a stretch to say that most of what happens in an introductory programming course is that students are presented with conflict-type feedback from programming software.

For this study, the control subjects were Marketing students in a consumer behavior class. In contrast to a programming class, a consumer behavior class has behavioral feedback, and much less feedback in general. While the lecture part of each class might be similar, the homework part of each class is very different with respect to conflict feedback. In consumer behavior (and most other classes) the general rule is one set of feedback per assignment. However, in programming the feedback is constant. Thus, one difference is that the feedback is offered in real time by a computer rather than asynchronously by a human being. The other difference is that human beings are much more flexible in their understanding, whereas the computer requires perfection for understanding. Therefore, if a student forgets a semicolon in a consumer behavior class, there will be little or no loss of understanding, and indeed it may not even be noticed. However, if a student forgets a semicolon in a programming course he will immediately receive feedback that his program does not work and may be reminded many times until the conflict is resolved. This leads us to hypothesize:

MIS-Marketing Hypothesis: Subjects taking a course in programming will show a larger increase in prefrontal cortex to anterior cingulate cortex connectivity than subjects taking no programming course.

METHOD

² This type of intelligence, the emotion monitoring part of “emotional intelligence” (Mayer et al. 2008; Roberts et al. 2010), is important in its own right, but is one we do not address in the present research. Our concern is simply whether people trained in computational thinking are more effective in conflict monitoring and control.

We begin our method section with basics on diffusion tensor imaging since, to our knowledge, this is the first study utilizing this methodology in the mainstream MIS literature.

Diffusion Tensor Imaging Basics

Diffusion Tensor Imaging (DTI) is a means of acquiring information about white matter tracts from a magnetic resonance (MR) machine. We offer a brief overview of the technique here, but necessarily leave out many details that are of more interest to MR physicists and neuroanatomists.

The brain is made of many types of cells, including neurons. Neurons are believed to be the cells of thought. They have a head with many branches and a long tail called an axon. The axon allows a neuron to connect with other neurons at a distance. Roughly speaking the neurons are arranged like lily pads on a pond with the heads on the top surface and the axons, like roots, stretching down below. As noted, the outside layer is termed “gray matter” and the connections that run beneath are called “white matter.” The white matter is arranged in bundles called white matter tracts, which, as noted earlier, connect different areas of the brain to allow them to communicate. Within each cell is water, which allows us to measure the location and orientation of white matter.

DTI is based on the physics of diffusion of water. If unobstructed, water tends to diffuse in a random manner called Brownian motion. However, when water is blocked by a barrier it cannot diffuse in an unrestricted manner. Neurons have long thin axons, which allow water to diffuse along the lengthwise direction, but which block water in other directions (see Figure 1).

A magnetic pulse applied to water returns a signal that varies with the diffusivity of water in the direction of the pulse. The more water is free to diffuse, the stronger the signal, and the more restricted, the weaker the signal. If a pulse is applied in a variety of directions, the relative diffusivity of water in each of those directions can be determined. Such a measure allows a diffusion tensor describing the relative amount of diffusivity in the x, y, and z directions to be created.

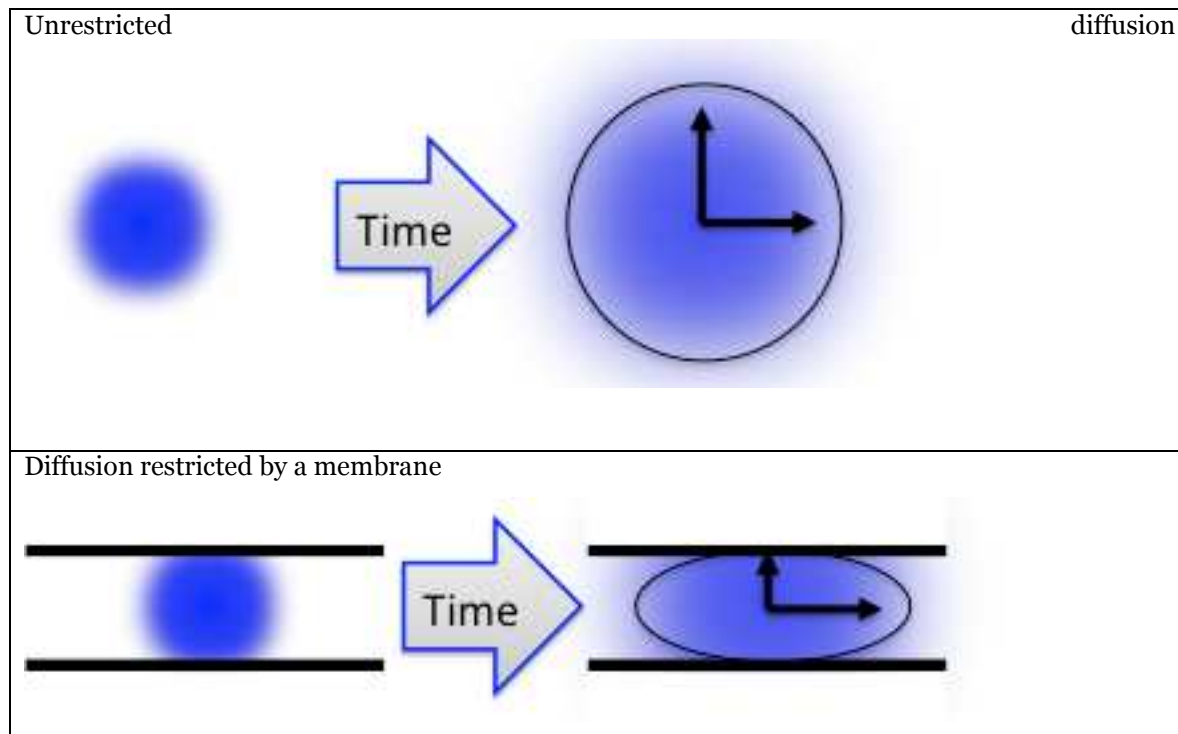


Figure 1: Difference in diffusion of water in the presence and absence of a membrane, as in the axon of a neuron

The entire brain of a person can be scanned in cubes called voxels, which measure a few millimeters on each edge. A diffusion tensor is then created for each voxel. These tensors are three-dimensional

representations of the diffusivity and can be thought of as ellipsoids. One of the pieces of information that can be recovered from the tensor is the primary direction of diffusivity in a voxel, which is the long direction of the ellipsoid. By tracing the direction of flow from one voxel to the next, one can trace entire white matter tracts.

However, there are two issues that we address before tracing the tracts. The first issue is noise. Measures are not perfect for a variety of reasons, so our estimate of the main direction of diffusivity will contain noise. Thus, instead of estimating a single direction of diffusivity, we estimate a distribution of directions. This leads to the possibility of estimating different paths.

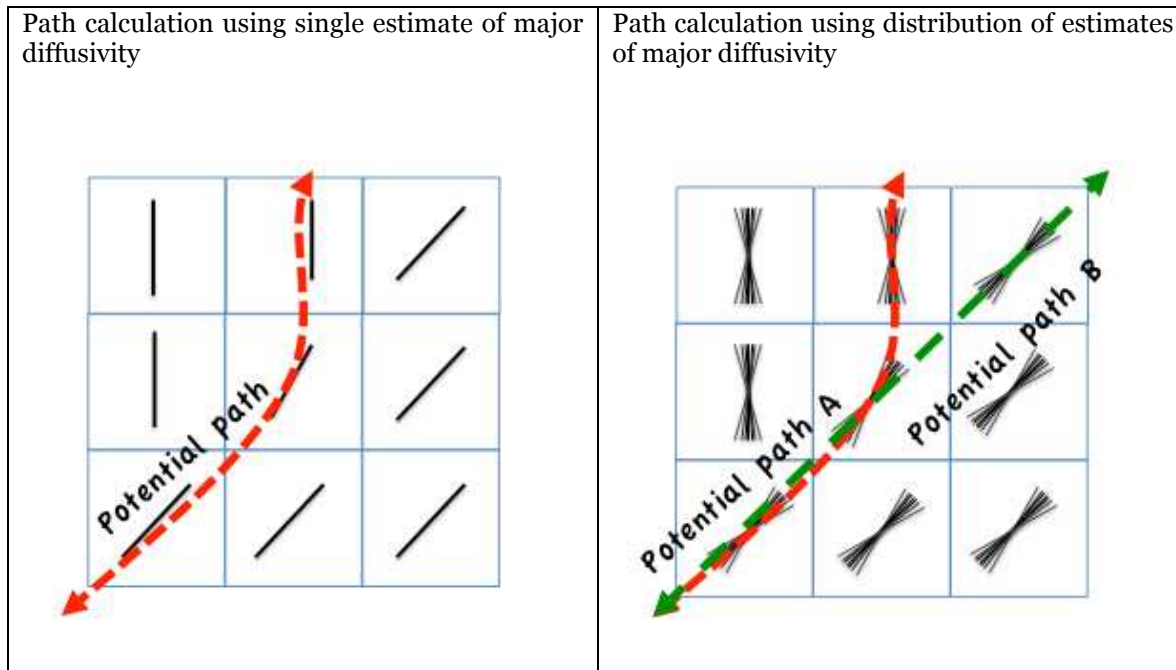


Figure 2: Hypothetical Diffusion Paths

The second problem we face is the issue of crossing voxels. Within any particular voxel there may be many white matter fibers. These different white matter fibers may be aligned in different directions. For example one white matter tract running inferior-superior (bottom to top) might cross another running anterior-posterior (front to back). In the voxel in which the crossing occurs, the average direction of diffusivity will be the average of the two tracts, but what really occurs is that there are two separate tracts. As an analogy, we can imagine a street intersection. On the main roads the average direction of traffic is clear, but at the intersection the average direction of traffic is a poor representation of reality. This is illustrated by the center voxel (labeled A) in Figure 3. Taken alone, this voxel would suggest no particular direction of diffusivity. However, when the whole picture is considered, it appears that there are two distinct tracts—one in each diagonal direction—that cross at voxel A. Thus, rather than assume a single principal direction of diffusion, we instead assume A is a crossing voxel and calculate two diffusion directions.

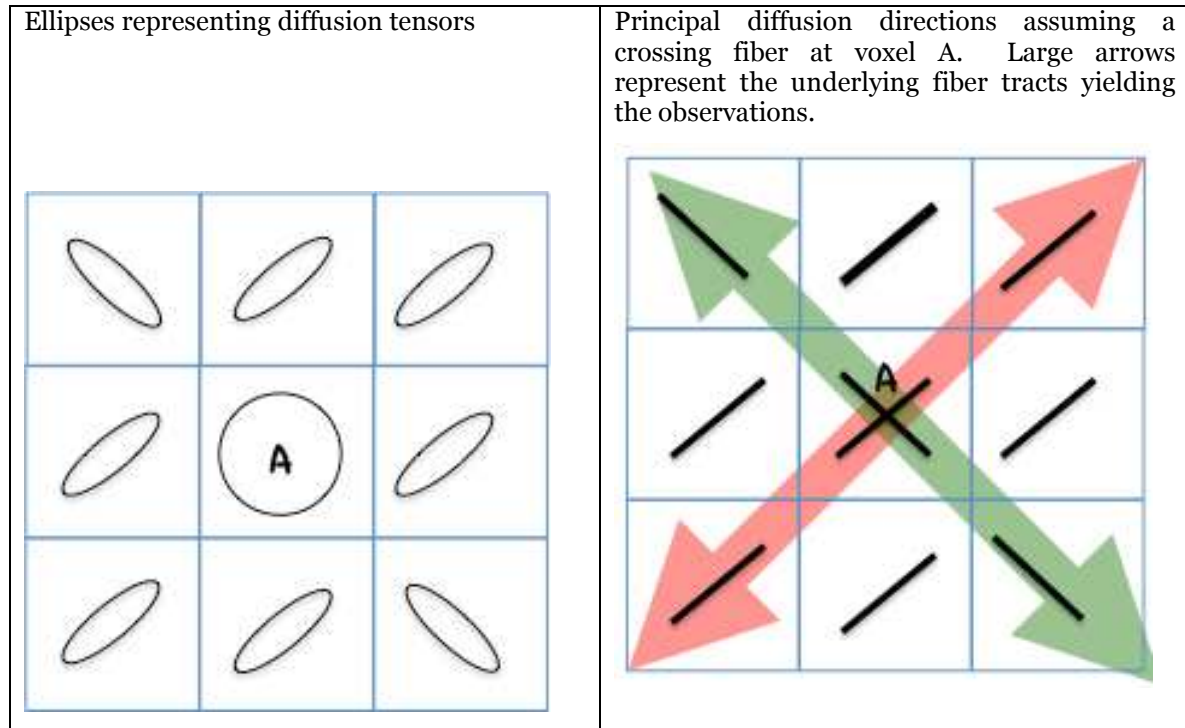


Figure 3: Different diffusion tracts

If we allow for crossing voxels, then for each voxel we can calculate multiple directions of diffusion, though it is usually limited to two, and only in voxels in which it seems likely that there is crossing. This allows for more potential paths as illustrated in Figure 4.

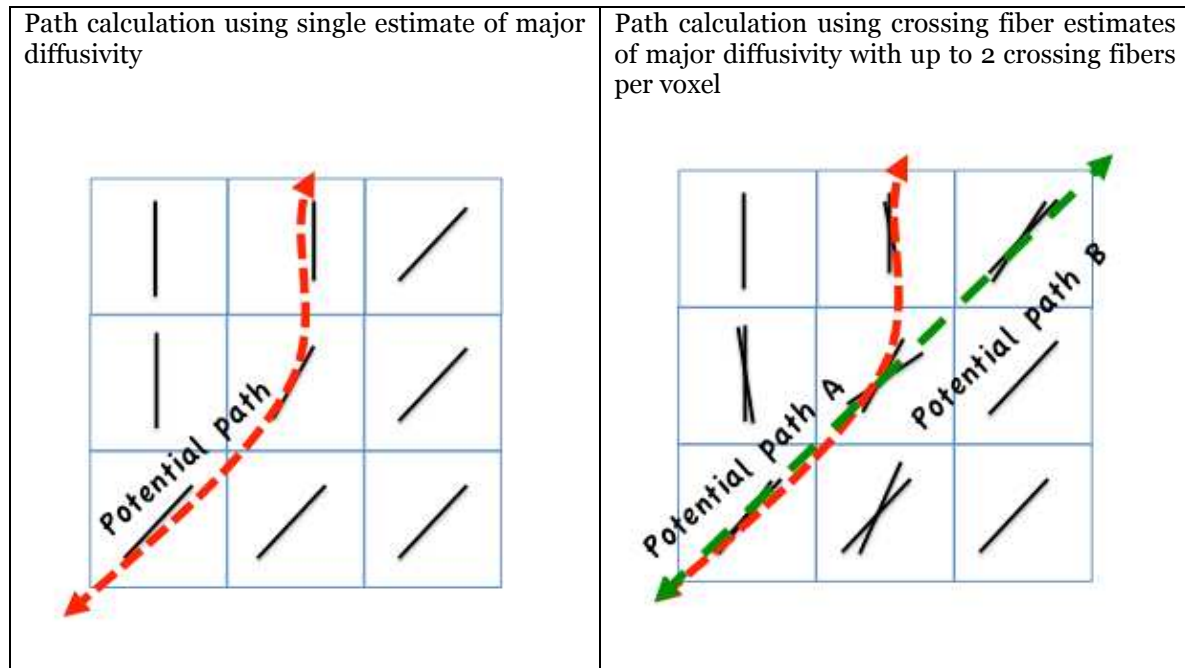


Figure 4: Potential paths with crossing voxels

Given that each voxel may contain a crossing fiber and that each principal direction may be estimated as a probability distribution rather than as a scalar, we are left with a complex map of the brain. At each voxel, of which there may be 100,000 or more depending on resolution, we have two empirical distributions of direction. Typically, 5000 draws are used to calculate each empirical distribution, which results in up to 10,000 different vectors per voxel.

Based on our theory and hypotheses presented earlier, we investigate whether there are connections between particular brain regions. Thus, we identify two different voxels and trace the directions of diffusivity. However, if there are multiple directions and hence multiple possible paths available, then discovering a path between two voxels becomes probabilistic. To address this issue we start our trace at the first voxel of interest, then randomly choose the direction from the range of possible directions and continue until we either terminate or reach the other voxel of interest. If we repeat this many times then we can simply divide the number of times the path was reached between the two voxels by the number of trials to assess the probability that the two voxels do indeed have a white matter tract connecting them.

For our study we used FSL's DTI software, which consists of several modules. BedpostX (Bayesian Estimation of Diffusion Parameters Obtained using Sampling Techniques) calculates the empirical distribution and crossing fibers. ProbtrackX samples from the output of BedpostX to generate probabilistic paths from voxels of interest. Full details of these models and methods are described in ([Behrens et al. 2007](#); [Behrens et al. 2003a](#); [Behrens et al. 2003b](#); [Johansen-Berg et al. 2007](#)) and the FDT User Guide (describing the FSL software modules).

Procedure

Our subjects were drawn from the business school at a large university. Seven subjects were drawn from MIS students who were taking their first programming course. In this case, the course covered Java, and was taught in a seven-week format by a veteran instructor unaffiliated with this study. The subjects were acquired over two semesters of the Java course—four in the fall semester and three in the spring semester of the same year (with the same seven-week course and same instructor in both semesters). The control subjects were drawn from the same business school by advertising in a consumer behavior class in the Marketing department. Five control subjects were all scanned in the same fall semester as the first four MIS students. Both groups were scanned twice seven weeks apart. It is worth noting that this sample size is representative of studies of this type (e.g., Behrens et al. 2003a used eight subjects, Schlaug et al. (2009) used six).

The students were of course engaged in many activities other than simply learning Java or consumer behavior. In fact, it is likely that they were also taking other courses in their chosen majors during the same time. Thus, we must be careful in attributing any changes in connectivity to the exclusive effects of learning Java or learning consumer behavior. We can only claim that the results are consistent or inconsistent with the theories of computational thinking outlined above. However, it is the case that at least one factor that could have caused differences between the two subject groups is the learning of computational thinking. That is, we may be observing more of the differences between MIS and Marketing students in their sophomore year than in the differences between Java and consumer behavior. This is why we were careful to name the comparative hypothesis the MIS-Marketing hypothesis. Even if this is the case, we are still comparing learning computational thinking and learning some other sort of thinking. We specifically drew from consumer behavior in Marketing as the foil to MIS rather than Accounting or Finance, both of which make extensive use of computer systems and formal rule systems.

Given that structural brain changes take time, it will be difficult to control for all possible alternative explanations in this type of research under any circumstances. However, we do look at students in the same area during the same time frame during the same time of their education. They are all business school students and have many similarities. The central difference is what they were learning in their programs at the time, which was MIS or Marketing, and our selection of subjects was specifically based on learning to program in Java or learning about consumer behavior. The Java group was very likely engaged in much more learning related to computational thinking than the consumer behavior group.

The twelve subjects were scanned twice for a total of twenty-four scans using a 1.5 tesla GE Signa Excite scanner. First, we acquired high-resolution T1 scans with a resolution of .94 X .94 X 1.5 mm in 116 slices with a field of view of 256 mm. The TR/TE was 25/5 ms, with a flip angle of 40°. We then acquired diffusion weighted scans in 55 directions with a diffusion gradient of 1000 s/mm². The field of view was

256 mm, voxel size was 1.3 X 1.3 X 4.5 mm, and there were 34 slices. The TR/TE was 10000/95.8 ms, with a flip angle of 90°. We used a standard brain template, the Montreal Neurological Institute (MNI) brain, to define our areas of interest as shown in Figure 5 below. Because each individual has variations on brain shape, we calculated a warp field that deformed the MNI brain into the same shape as each subject's brain and then used these areas to perform probabilistic tractography.

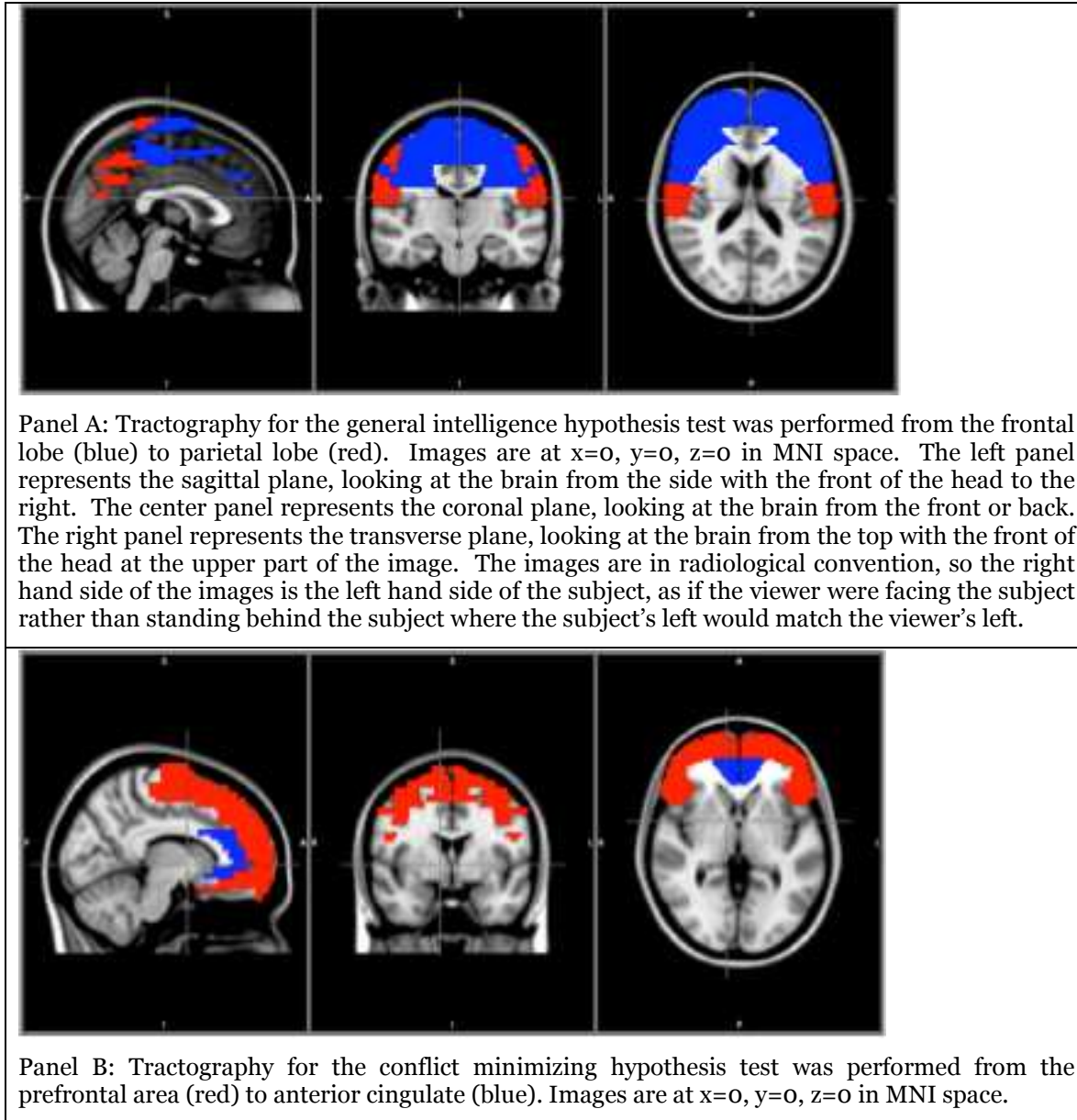


Figure 5: Regions of interest for the general intelligence hypothesis (Panel A) and the conflict minimizing hypothesis (Panel B).

For each voxel in one region 100 paths were traced. Those that passed through the other region were counted. There were 44,976 voxels in the prefrontal area so 4,497,600 total paths were traced for each subject. There were 70,324 voxels in the frontal lobe so 7,032,400 paths were traced for each subject.

We calculated the average number of connections per hundred samples. Roughly speaking, this is the probability that a randomly sampled voxel in one region from a randomly sampled subject would show a white matter projection into the other region. This is our estimate of connectivity.

RESULTS

Results showed that there was a significant increase in connectivity between the frontal and parietal regions for the MIS group after the semester ($t = 4.84, p < 0.001$), as shown in Figure 6. This is consistent with the general intelligence hypothesis above, which suggests that connectivity between these two regions should increase with training in computational thinking. There is also a significant increase in connectivity for the Marketing student group ($t=6.43, p < 0.001$), which is consistent with the P-FIT theory notion that parietal-frontal integration is important for intelligence, which is presumably enhanced by being in college. However, there is not a significant difference between the two groups ($t=0.65, p = 0.51$). This is consistent with the perspective that a college education makes people generally more intelligent, but that neither MIS nor Marketing education is better at increasing intelligence.

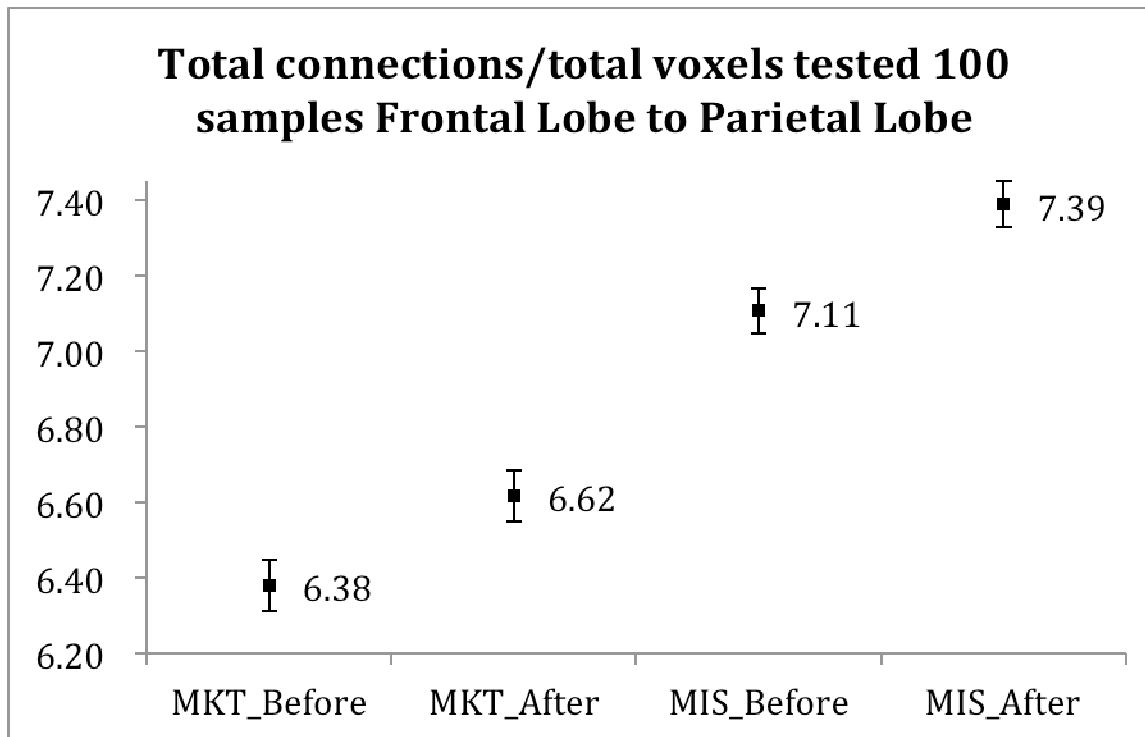


Figure 6: Connectivity between the frontal and parietal lobes (95% confidence interval indicated by vertical error bars)

There was a significant ($t=7.27, p < 0.001$) increase in connectivity between the prefrontal and ACC areas for the MIS group after learning Java. This is consistent with the *Conflict Minimization Hypothesis* above, which suggests that computational thinking involves learning how to reduce conflict between behavior and (computer) outcomes. There was a non-significant ($t=0.81, p=0.42$) drop in connectivity measured for the Marketing group (see **Figure 7**).

As hypothesized, there was a significant ($t=5.23, p < 0.001$) difference in connectivity from the prefrontal cortex to the anterior cingulate cortex between the MIS and Marketing groups. This is consistent with the *MIS-Marketing Hypothesis*, which supports the notion that learning Java (and likely programming more generally) strengthens the connectivity between regions involved with conflict avoidance more than learning consumer behavior (or Marketing more generally).

To summarize the results, we find that connectivity between regions associated with intelligence in general increase for both people learning marketing and people learning to program. However, the amount of the increase is the same for both groups. Essentially, this suggests that both groups got smarter from learning. Smarter in this case means having an increased potential communication bandwidth between the frontal and parietal lobes. On the other hand, when we look at the potential bandwidth between the executive regions and regions that handle conflict resolution, only the people who

learned programming got smarter. In other words, learning to program had a specific effect on the structure of student's brains.

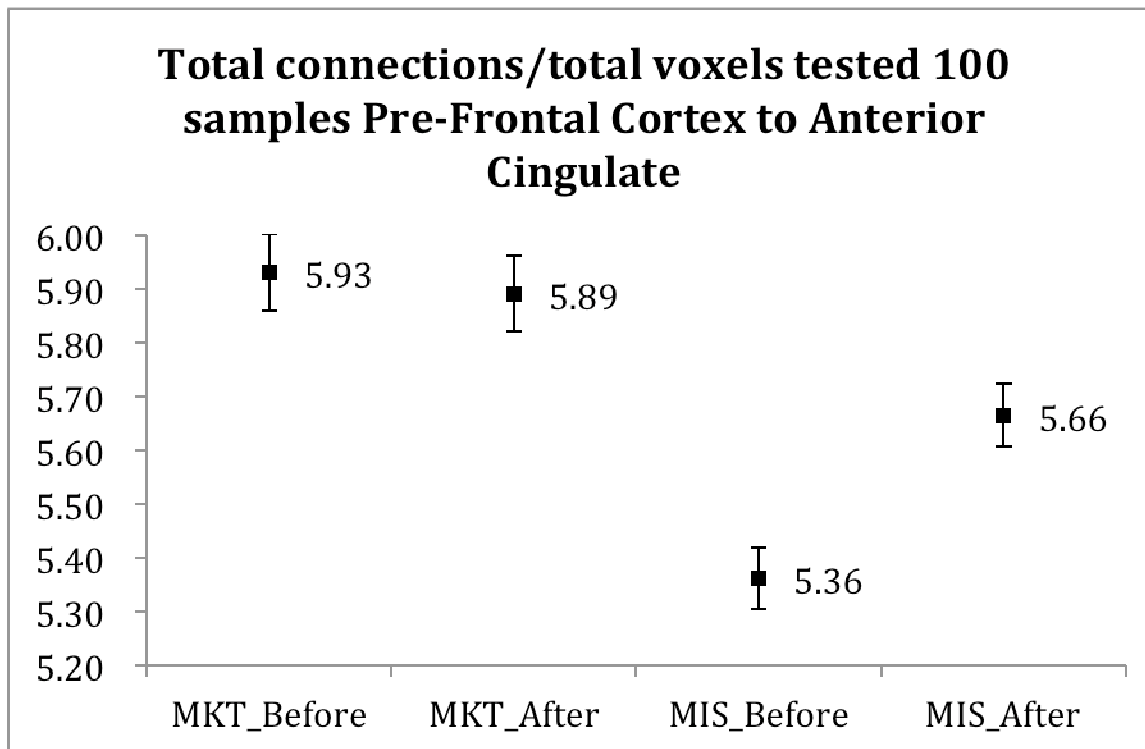


Figure 7: Connectivity between the pre-frontal cortex and anterior cingulate (95% confidence interval indicated by vertical error bars)

DISCUSSION

Taken as a whole, these results are consistent with the idea that computational thinking is a special type of thinking different from intelligence in general. Both MIS and Marketing students showed increases in connectivity associated with intelligence in general, but only the students learning programming showed increases in connectivity between the prefrontal regions and the anterior cingulate cortex, which is associated with conflict avoidance and resolution. Anticipating and avoiding conflict between different software artifacts is a large part of what MIS professionals and computer scientists do in their jobs. We will go so far as to say that one of the primary factors that separates skilled computing professionals from the unskilled is the ability to anticipate and avoid creating conflicts among software artifacts. Our results support the value of training in programming to improve conflict avoidance skills.

The Carnegie Mellon Center for Computational Thinking states that, “*Computational Thinking is the thought processes involved in formulating problems and their solutions so that the solutions are represented in a form that can be effectively carried out by an information-processing agent*” (Cuny et al. 2010). Our sample suggests that the structure of the brain mirrors this definition. Roughly speaking the prefrontal regions handle “*thought processes involved in formulating problems and their solutions,*” while the ACC makes sure these solutions “*can be effectively carried out,*” with effective meaning “low conflict.” Of course, “effective” could also mean that the information-processing agent performs something useful or appealing to human beings, but it is likely that such a skill would come much later in the educational process. And, realistically, choosing the right problems to solve is a rare and valuable skill that many people never develop.

The purpose of this work is not to end the inquiry into the neural mechanisms of computational thinking, but rather to begin the inquiry. There are many directions for future research that are worthwhile.

First, we only investigated connectivity between two pairs of regions. There are many areas of connectivity that we can examine. In fact, there are too many. With 50,000 voxels per brain volume, one could potentially measure connectivity between 1.25 billion different combinations of single voxel regions, and if we allow regions to be more than a single voxel and of different sizes that number of potential regions of connectivity becomes much larger. However, a principled investigation of other regions of connectivity based on theory about what computational thinking involves and the functions other brain regions perform would be worthwhile.

The usual cautions about a single study also allow room for future work. It would be worthwhile to see if these results are replicable in other samples. It may be the case that our sample was somehow unique, and we cannot know without replications of this work.

It would also be worthwhile to try to isolate programming training. Ideally, we would like to choose a random sample and teach a random group to program while giving the other group an equal but non-computational education. In this work we chose subjects based on their enrollment in one of two courses, but we did not randomly control for outside influences. The difficulty is that teaching computational thinking takes some time, and structural changes in the brain also take time. Over a period of months it becomes difficult to control for outside influences. Moreover, such a study would be extremely costly. Nonetheless, such a study would be the gold standard for investigating the effect of learning programming.

Another avenue of future research would investigate professional computational thinkers rather than people learning computational thinking. While it seems reasonable to assume that computational thinking can be learned, it may be that something else is actually learned in an introductory programming course. To control for this a future study could compare people who are known via other measures to be computational thinkers to people who are known not to be. This could perhaps be deduced through a behavioral or personality test. Alternatively one could take successful professional programmers and compare them to people in other lines of work. However, this reintroduces the problem of confounding factors. There might be systematic differences between programmers and others that are not based on computational thinking.

The best course of action is to pursue all of these lines of inquiry. Any individual method has weaknesses, and any specific design has even more weaknesses. The goal of research should be to validate in many different ways. This research offers a single way to look at the neural mechanisms of computational thinking, and like any method has weaknesses. However, taken as a starting point for inquiry, this work offers a powerful contribution to knowledge.

While this work is primarily academic, it also has practical implications for information systems education and computational thinking. This is important because the modern economy is driven by computer technology, and we cannot sustain growth and improvements in productivity without a large pool of computational thinkers.

One practical implication is that minimizing conflict seems to be an important part of computational thinking. Thus, it is worth exploring whether increasing focus on conflict minimization might increase the effectiveness of information systems development. Conflict minimization is a task that is described as a preventative focus ([Brockner et al. 2001](#)). The type of feedback provided influences motivation for preventative focused tasks. Positive feedback has been shown to decrease the motivation for preventative tasks, while negative feedback increases it ([Van-Dijk et al. 2004](#)). Thus, if conflict reduction is very important to computational thinking, negative feedback might be better than positive feedback at motivating performance.

Overall, this introductory work on the neural mechanisms of computational thinking has offered important academic and practical insights. We make two important contributions. First, we have demonstrated the usefulness of the DTI neuroscience method for understanding problem solving in an IS context. The DTI method holds much potential for explaining the underlying cognition for many behavioral IS phenomena. Second, we make an important contribution to understanding computational thinking. Increased connectivity between the prefrontal regions and the anterior cingulate cortex is a distinguishing mark of computational thinking in our sample. This suggests that effective communication between regions of the brain that handle executive functions and those that deal with conflict minimization are important for computational thinking. Given motivational differences in conflict

minimization tasks, this paper offers a basis for exploration of better methods for information systems development. We have offered not only important and novel contributions to knowledge, but also a springboard for future research.

We would like to conclude by making a call for more research on this topic. These results are exploratory and are based on a small sample. Understanding how learning to program changes the human connectome should be a fundamental question for IS scholars in years to come as we now have the technology to address this question. This research should not be the last word, but rather the first word in an ongoing exploration of how what we teach impacts our students.

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