How Learning Experience Shapes the Cognitive and Neural Representations of Letters

by

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Abstract

This dissertation furthers our understanding of the nature of conceptual representations in the mind/brain, specifically with regard to the debate between grounded and abstractionist theories of cognition. Grounded cognition theories range from reductionist views that propose that concepts have only sensory/motor representations, to less reductive views that allow for amodal representations, although positing that these necessarily interact with modality-specific processes. Opposing abstractionist theories propose that conceptual processing is carried out with symbolic, amodal representations, interacting with sensory/motor processes only as context demands.

This issue was examined in the domain of letter processing, where previous research has indicated that writing experience is more beneficial than non-motor experience for learning letters. The dissertation research includes a longitudinal training study with behavioral and neuroimaging analyses, designed to reveal the content of letter representations and how these are affected by different letter-learning Conditions: Typing, Visual, or Writing. The results address the following questions about the role of writing experience in letter learning: (1) Are the effects of writing experience due to motor learning *per se*, or to other variables confounded with the writing experience? (2) Does writing experience recruit only sensory/motor representations? (3) Which types of representations, motoric or otherwise, underlie the behavioral benefits of writing experience?

I conclude that the evidence supports the view that cognition involves both groundedness and abstraction. Sensory/motor representations were found to be recruited for letter perception, and moreover were associated with behavioral performance on letter processing tasks. This argues against a strong abstractionist claim that sensory/motor activity is epiphenomenal. However, symbolic, amodal letter identities (SLI) were also associated with behavioral performance, and were strongest in the Writing Condition. These results challenge grounded theories that reduce concepts to sensory/motor representations, and support the existence of conceptual representations that are truly amodal.

On the basis of these findings, I propose that writing experience is particularly beneficial to learning letters because it strengthens connections between various modality-specific letter representations, mediated by amodal SLI representations. I discuss the implications of these results for theories of cognition, educational practice and future directions for research.

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Introduction

This dissertation examines aspects of the nature of conceptual representations that are relevant to a fundamental debate in cognitive science regarding the role of sensory/motor representations in conceptual processing—the debate between grounded cognition and abstractionism. Specifically, the dissertation examines evidence arising from the role of learning experiences (writing, typing, or visual study) in letter acquisition. It does so by conducting a longitudinal training study including both behavioral and neural measures of letter learning. Previous research on this topic has suggested that writing experience is more beneficial for learning letters compared to other, non-motor learning experiences (Bhide, 2018; James & Atwood, 2009; James & Engelhardt, 2012, 2012; Li & James, 2016; Longcamp et al., 2008; Longcamp, Zerbato-Poudou, & Velay, 2005; Longcamp, Boucard, Gilhodes, & Velay, 2006; Naka, 1998; Naka & Naoi, 1995; Zemlock, Vinci-Booher, & James, 2018), providing benefits to letter recognition, categorization, and retention. These findings have been argued to support theories of grounded cognition, which posit a necessary role for sensory/motor representations in conceptual processing (James, 2010, 2017; James & Gauthier, 2009; Loeffler, Raab, & Cañal-Bruland, 2016; Longcamp, Tanskanen, & Hari, 2006; Mangen & Balsvik, 2016). However, earlier work has not clearly established that the observed benefits are specifically due to motoric representations resulting from the writing experience, as would be predicted by grounded cognition. In order to address this outstanding issue, the work reported here goes beyond tasks of letter recognition and categorization to more deeply assess the impact of different learnings experience on letter processing. Additionally, it represents the first investigation of the consequences of writing experience for the *content* of letter representations, both in terms of behavioral consequences, evaluated through letter perception tasks, and in terms of neural activity, evaluated using Representational Similarity Analysis (RSA, Kriegeskorte, Mur, & Bandettini, 2008).

The study design and analytic techniques allow for testing the following unresolved questions about the role of writing experience in letter learning: (1) Are the effects of writing experience due to motor learning *per se*, or to other variables confounded with the writing experience? (2) Does writing experience recruit only sensory/motor representations? (3) Which types of representations, motoric or otherwise, underlie the behavioral benefits of writing experience? The answers to these questions have important implications for understanding the nature of conceptual representations in general, letters being simply an example of an object category that has conceptual representations. Moreover, letters are particularly relevant for this debate, as they are associated both with information in multiple modalities (e.g., visual, motor, auditory) and abstract information (e.g., their identities). There are also important practical implications of this research, as evidenced by the interest of both the popular press and education researchers in findings about the role of writing experience' in letter learning (Berninger et al. , 2006; Deardorff, 2011; Konnikova, 2014).

What Do We Know About Letters?

It has been estimated that, reading an average of one hour per day, a middle-aged adult will have encountered roughly one billion letters (Pelli et al., 2006). This vast amount of exposure makes letter processing an ideal topic for studying how experience affects conceptual representations. Letters are not only a worthy subject because of our extensive familiarity with them, they are also fairly complex objects, despite the relative simplicity of their geometry. Their complexity stems from the wealth of information we have about letters. For a single letter like [A] we know that: this letter can look like 'A' or like 'a'; it may be written beginning with an upward stroke slanted to the right; its name is /ei/ but in English it can represent the sounds /æ/ or /ɑ/; it is the first letter of the alphabet; on the keyboard it is situated to the left of [S] on the center row; and as an English word it indicates the indefinite article.

This simple object, which typically appears in the real world as just a few black lines, evokes knowledge and processes that involve representations in multiple sensory modalities (visual, auditory, motor), as well as representations of abstract properties (e.g., identity, case, etc.). We use letters for multiple tasks, such as reading, writing, and spelling, in ways that involve numerous cognitive processes: visual processing for letter detection and identification, phonological processing for spelling to dictation, motor planning for writing and typing, etc. It is well-established that better letter knowledge among young children (pre-K and kindergarten) is predictive of reading and writing skills even into middle school years (Bara & Bonneton-Botté, 2018; Berninger, Abbott, et al., 2006; Treiman & Kessler, 2004; Treiman et al., 1998; Zemlock et al., 2018). Given the importance of learning letters, there has recently been concern that changes in technology and elementary school curricula may have a negative impact on reading and writing skills. Letters have traditionally been taught in tandem with handwriting, but time spent teaching this skill has been vastly reduced (Deardorff, 2011; Konnikova, 2014), and both children and adults spend more reading and writing through digital formats, rather than through pen and paper. Thus, understanding how letter processing is affected by learning experience, and in particular writing experience compared to typing or non-motor experiences, has important educational implications.

Grounded Versus Abstract Cognition: The Nature of Conceptual Representations

In recent years, cognitive scientists have debated between theories that all fall under the umbrella of "grounded cognition" (Pecher & Zwaan, 2005) and opposing abstractionist theories. The impetus behind grounded cognition theories may originally have been Searle's "Chinese Room" (Searle, 1980)[1], which was concerned with the fundamental issue of how symbols get their meaning and relate to the real world outside of the mind/brain. It is considered to be a critique of the prevailing abstractionist theories of cognition at that time, which held that cognition was symbolic in nature. The problem posed by Searle's thought experiment has come to be known as the "symbol grounding problem" (Harnard, 1990). The issue can be posed as the question: What is the content of conceptual representations? The term "concept" here is used to refer to the representations and processes used to relate mental states to categories outside of the mind (following Barsalou, Simmons, Barbey, & Wilson, 2003). Concepts can be concrete, meaning they have referents in the physical world and thus are associated with sensory or motor information. Members of concrete concepts

[1] Searle's "Chinese Room" (1980) contested the assumption of symbolic artificial intelligence that a machine with a symbolic system (i.e., that carries out computations by manipulating abstract symbols) able to pass the Turing test must therefore have a mind. Searle's thought experiment consists of supposing that if he himself were given the computer's translation program in the form of an English-language manual, he too would seem to understand Chinese—despite not speaking a word of Chinese. The argument is thus that the meaning of symbols, such as the Chinese characters, is not intrinsic: their shapes convey no meaning or only do so through reference to objects in the real world. Therefore, human cognition cannot be purely symbolic or else it would be devoid of meaning or understanding. See (Harnard, 1990) for further explanation.

are distinguished from non-members by sensory/motor information—for example, a lemon but not a lime is associated with the concept [yellow] by virtue of perceived color. Other concepts are abstract, which are "irreducible to sensory-motor properties not by virtue of being invisible or inaudible, but because they form categories whose members are heterogeneous in their sensory-motor qualities" (page 997, Leshinskaya & Caramazza, 2016). Thus, for example, sensory/motor information is insufficient to explain why dandelions and poison ivy, but not daisies or grape vines, are associated with the concept [weed]. The main contention relates to the question of the content of conceptual representations. There are three main types of representations that have been proposed:

(1) *Amodal representations:* Concepts may be represented by amodal symbols, meaning the representations contain no information about any specific modality, and relate only arbitrarily to the real world. Amodal representations therefore have no intrinsic meaning and are ungrounded, in the sense of the symbol grounding problem. Amodal representations are well-suited for abstract concepts, which by definition have no concrete physical referents. However, amodal representations are not limited to abstract concepts, as some have proposed a role for them even in concrete concepts such as color (see Leshinskaya & Caramazza, 2016).

(2) *Modal representations:* Concepts may be represented in terms of the modalities through which humans receive sensory information (e.g., visual, auditory) and produce responses (e.g., motoric), hence the term "sensory-motor"[2]. In some grounded cognition views, the

[2] Although the term "sensory-motor" with a hyphen is in common parlance, I find it to be somewhat misleading, as it can suggest representations that are simultaneously sensory and motoric (see: multimodal representations), and may

modal representations may be extended to include other ways through which we experience the world (e.g., social context, affective state, appetite) (see Barsalou, 2016). Modal representations are grounded by default; however, they are less obviously sufficient for representing abstract concepts that do not have concrete referents.

(3) *Multimodal/supramodal representations:* Information from multiple modalities may be combined to create a multimodal representation. A multimodal representation, alternatively called "supramodal", does not contain information about any *single* modality, but rather combines information from multiple modalities into a new representation. This representation may include only partial information about any individual underlying modality. Nonetheless, because at least some modality information can be retrieved from multimodal representations, they remain grounded. Various mechanisms have been proposed by which multimodal representations may come to represent abstract concepts (see Chapter 1).

In contemporary cognitive psychology, grounded cognition theories seek to resolve the symbol grounding problem by proposing that all concepts depend on modal and/or multimodal representations. This is held to be true even if the concepts refer to abstract entities. The various hypotheses differ in the degree to which they allow for non-sensory/motor representations to play a role in cognition. The "strongest" grounded cognition claims reduce all concepts to sensory/motor representations (Barsalou, 2016;

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obfuscate distinctions between cortex that is primarily somatosensory and cortex that is primarily motor. Henceforth I use the term "sensory/motor" with a slash, to instead indicate representations that are sensory *or* motoric, but not necessarily both.

Barsalou et al., 2003; Leshinskaya & Caramazza, 2016). The "weakest" grounded cognition claims allow for the existence of amodal representations for certain concepts, but stipulate that conceptual processing still fundamentally relies upon modality-specific representations (Barsalou, 2016). Opposed to grounded cognition are abstractionist theories, which have in common the claim that all concepts have amodal symbolic representations[3], and thus are deeply at odds with strong grounded cognition claims.

One of the most well-known grounded cognition theories is "embodied cognition" (Varela, Thompson, & Rosch, 2000), which falls on the side of strong grounded cognition. Embodiment proposes that all concepts are related to the outside world in terms of the body: how objects and events are perceived via human sensory organs, and how the body physically interacts with and is situated in the external environment. In its most extreme form, embodied cognition holds that concepts reduce entirely to sensory/motor representations—"conceptual processing *already is* sensory processing" (60, Mahon & Caramazza, 2008). Although a strong embodiment theory solves the symbol grounding problem, it raises the problem of how modal representations alone can support abstract concepts (Barsalou, 2016; Leshinskaya & Caramazza, 2015, 2016; Wilson-Mendenhall,

[3]This is not a statement that abstractionist theory rejects sensory/motor representations. On the contrary, sensory/motor representations are certainly though to exist and to be important, with respect to concrete concepts (e.g., color). The argument is that the "human mind must have… something that allows thinking to proceed unencumbered by our representations of our body and the world" (421, Mahon, 2015). Thus, while there are certainly sensory/motor representations of concepts like color and shape, the claim is that there must also be separate conceptual processes to allow cognition about such concepts in the abstract. The representations used in these processes are, under abstractionist theory, amodal. This is opposed to grounded cognition views, which maintain that (a) any concept that does have concrete referents, like for color concepts, need not have an amodal representation, and therefore must not; and (b) even abstract concepts without obvious sensory/motor referents can still be instantiated through modality-specific representations. Discussion of proposed mechanisms by which abstract concepts could do without amodal representations is presented in Chapter 1.

Simmons, Martin, & Barsalou, 2013). Therefore, many grounded cognition theories adopt a less extreme position, allowing for abstract concepts to be represent by wider range of modalities beyond the sensory/motor ones, by multimodal representations, and the existence of certain amodal representations (Barsalou, 2016; Binder, 2016; Martin, 2016; Zwaan, 2016). In particular, amodal representations are granted for some concepts that "represent information that is common across modalities" (page 1127, Barsalou, 2016), such as magnitude.

Arguably, the clearest difference between grounded cognition and abstractionist theories relates to the nature of modal-amodal interactions. Under abstractionist accounts, like in Searle's "Chinese Room", cognitive processes can operate exclusively on amodal representations, without any grounded, extrinsic referential meaning. Alternatively, according to grounded accounts, cognitive processes that make use of amodal representations *mandatorily* interact with modal representations (Barsalou, 2016; Leshinskaya & Caramazza, 2016; Mahon, 2015; Mahon & Hickok, 2016). Further discussion of the different proposals under both types of accounts is presented in Chapter 1.

Grounded cognition theories have been put forth to explain a number of cognitive psychology and neuroscience phenomena, including ones examined in this dissertation. One phenomenon widely reported in neuroimaging studies over the last two decades is that areas of the brain traditionally associated with sensory/motor processing activate during tasks that would not seem to require sensory/motor information (see e.g., Barsalou, 2016; Dove, 2016; Goldinger et al., 2016; Mahon & Hickok, 2016). For example, in response to simply reading action verbs like "lick", "pick", and "kick" (for a review see Pulvermüller, 2005), activity in motor cortex reflects somatotopic arrangement (i.e., regions associated with motor responses for the face, arms, and legs, respectively). Although not often used as a key example in the ongoing debate, one domain in which this is consistently found to be the case is letter processing. For example, individuals viewing single letters while undergoing functional MRI (fMRI) show activation in "sensory-motor" areas implicated in written production (James & Atwood, 2009; James & Engelhardt, 2012; James & Gauthier, 2006; Kersey & James, 2013; Longcamp, Anton, Roth, & Velay, 2003; Longcamp, Hlushchuk, & Hari, 2011; Longcamp et al., 2006; Vinci-Booher & James, 2016; Vinci-Booher, James, & James, 2016). The specific areas of activation during letter processing tasks, including during passive viewing, have included primary motor, premotor, and supplementary motor cortices which have been implicated in planning writing movements (Planton, Longcamp, Péran, Démonet, & Jucla, 2017; Roux et al., 2009; Wamain, Tallet, Zanone, & Longcamp, 2012).

These results are often explained by appealing to grounded cognition, as these types of findings are consistent with the claim that conceptual processing requires the re-instantiation of modality-specific representations (Bhide, 2018; Li & James, 2016; Longcamp et al., 2008, 2005; Longcamp et al., 2006; Naka, 1998; Naka & Naoi, 1995; Zemlock et al., 2018). With respect to the findings that writing experience affects letter learning, the claim from grounded cognition is that letter perception necessarily recruits the same network that is activated for writing letters, and that "handwriting experience plays a crucial role in the formation of the brain network that underlies letter recognition" (page 6, James, 2017).

Taken together, the findings that writing experience affects letter learning behaviorally, and the brain's response during letter perception, have led to a popular account that writing experience is beneficial, and perhaps even critical, for learning to read and write (Bhide, 2018; Deardorff, 2011; James, 2017; Konnikova, 2014). This account can be characterized as making three claims, deeper scrutiny of which raises questions regarding the soundness of the conclusion that it is writing *per se* that is beneficial for letter learning, and whether the benefits are due to representations grounded in sensory/motor information. Consider the first claim: (1) sensory/motor cortex is activated during letter perception. Such activity is not proof in itself that sensory/motor *representations* become active during letter perception—this is particularly true because "sensory-motor" cortex has been used to refer to a network of regions, not all of which are thought to be primary sensory or motor areas. This network has been termed the "visual-motor letter processing system" (James, 2017) and includes association areas such as the inferior frontal gyrus and superior temporal gyrus. This means that the location of neural activity alone is not sufficient to draw conclusions about what type of information is being represented—a point which has been made by critics of grounded cognition generally (Leshinskaya & Caramazza, 2016; Mahon, 2015; Mahon & Caramazza, 2008; Mahon & Hickok, 2016). It has not been ruled out, for example, that writing experience supports the learning of letter representations other than just motoric ones or ones used for visual-motor integration. The activation observed during letter perception could also reflect amodal representations of abstract concepts like symbolic letter identity (Lupyan, Thompson-Schill, & Swingley, 2010; Rothlein & Rapp, 2014; Wiley, Wilson, & Rapp, 2016)

Turning to the second claim: (2) sensory/motor cortex activation during letter perception is unique to individuals who have experienced writing those specific letters by hand. The evidence is actually that sensory/motor cortex activation following writing experience is different than what is observed following other learning experiences, *not* that there is no sensory/motor activity whatsoever in individuals who lack writing experience. It remains to be demonstrated whether and how the effects of writing experience on sensory/motor cortex relate to letter processing. Finally, the third claim: (3) behavioral performance on tasks of letter recognition and retention is superior after writing experience compared to non-motor experiences. This piece of evidence only supports grounded cognition given the assumption that it is some aspect(s) of the motor learning that cause the superior behavioral performance. However, it has not been demonstrated that there is any association between behavior and the representations learned through motor experience *per se*. Alternatively, the superior behavioral performance may be related to some non-sensory/motor representation. Indeed, the effects of writing experience may even be seen to stem from variables related to the experimental conditions of writing experience, incidental to the writing processing itself. For example, writing conditions tend to require more time on task than visual study conditions, and the effects of "writing" experience could be due simply to relatively greater exposure to the letter stimuli.

Explaining the Effects of Writing Experience on Letter Learning

Given that multiple studies have reported writing experience is beneficial for learning letters compared to other experiences, it is clear that some mechanism(s) must explain this benefit. As was previously indicated, the apparent benefits of writing experience for letter recognition, categorization, and retention have typically been attributed to fundamental properties of human cognition being grounded or embodied. Because grounded cognition posits that sensory/motor representations are necessarily recruited during conceptual processing, the assumption is then that motoric letter representations are recruited for letter processing tasks, including ones that do not require writing. The mechanism by which this would happen is perhaps most clearly articulated in Anderson's "neural reuse" hypothesis (Anderson, 2010; Barsalou, 2016; Martin, 2016). According to this hypothesis, conceptual processing is carried out by re-instantiating some of the same neural pathways that are implicated during perception and action. For example, conceptual representations of colors *require* activation of some of the same neural circuitry for perceiving color. This means that letter processing depends on re-instantiating perceptual processes (e.g., visual processes during viewing letters) and motor processes (e.g., movement planning processes during writing letters). It follows naturally from the neural reuse/grounded cognition hypothesis that writing experience better supports letter learning, because without it motoric letter representations/motor substrates are not available for this "neural reuse". However, this would seem to require the additional assumption that visual representations alone are somehow deficient, relative to the combination of both motoric and visual representations.

The views of abstractionist theory, on the other hand, do not make any assumptions about the mechanisms that would cause writing experience to better support letter learning than non-motor experiences. Therefore, while abstractionism provides an alternative account to grounded cognition in terms of what the content of letter representations may be, it does not provide an obvious account of why those representations may differ because of writing experience. There is, however, an account that has been put forth to explain similar effects that have been found in a domain outside of letter processing. Specifically, both writing and drawing have been found to provide benefits in memorizing word lists for subsequent tasks of recognition and recall (see e.g., Bodner & MacLeod, 2016; MacLeod & Bodner, 2017; Wammes, Meade, & Fernandes, 2016). These results are specific examples of what are known as the "production effect" (MacLeod et al., 2010). The production effect refers to the phenomenon of better retention of studied items that were produced during the time of study. For example, in memorizing a list of words, words produced orally will be better remembered than words that were not read aloud. The production effect can be considered to fall within the class of "generation effects" (Slamecka & Graf, 1978). The distinction between production and generation is that in generation, the studier decides what the to-be-remembered item is, whereas in production, the items are given but are subsequently (re)produced by the learner. For example, a production effect is obtained if the word "kitten" is presented visually and participants read the word aloud themselves. A generation effect is obtained if instead a *cue* for the word is provided ("What rhymes with mitten and means a young cat?"). It has been established that the effects of generation and production on learning are distinct, and in fact some evidence suggests that combining the effects leads to even greater benefits (for example, given the cue *and also* prompted to say the word "kitten" aloud; see Wammes, Meade, & Fernandes, 2016). That the production effect is not limited to oral production but has also been found to include benefits of both writing and drawing suggests a plausible link to the benefit of writing experience on learning letters.

The critical question of course is what mechanism underlies the production effect? The leading account is that of "distinctiveness processing" (Hunt, 2013; MacLeod & Bodner, 2017). Briefly, according to the theory of distinctiveness processing, the production effect arises from the fact that not only do participants have memories of the items presented to them, they also have memory traces of the *events* of studying, In other words, participants can attempt to recall not only what items they were presented with, but also what actions they performed while studying each of those items. If the participants produced distinct responses (made a unique response to each item), then those memories provide an additional heuristic during memory tests. Importantly, the distinctiveness processing account does not appeal to any tenets of grounded cognition, as it does not make assumptions regarding the content of conceptual representations—the memory of how an item was studied could include a representation of sensory/motor *or* amodal information. Instead, distinctiveness processing presents a potential mechanism underlying the effect of writing experience that does not make specific commitments regarding the content of the letter representations that are learned. As such, it provides a possible explanation for benefits that may be observed which would be compatible with an abstractionist position. More details on this theory are provided in Chapter 1.

Outline of the Dissertation

In summary, an active area of research in cognitive science, and the central point of contention in the grounded cognition-abstractionist debate, concerns the nature of conceptual representations in the mind/brain. According to grounded cognition, all concepts must have representations that tie them to percepts and ultimately to concrete referents outside of the mind. Without grounding in the modalities, sensory/motor or otherwise, symbolic processing does not allow for interaction with the physical world. According to abstractionist views, concepts are represented by amodal symbols—conceptual processing is grounded by interacting with sensory/motor processes, but only to the extent required for performing a particular task. Researchers on both sides of this issue generally agree that sensory/motor and conceptual processes interact; for example, that sensory/motor activity can lead to activation of concepts and vice versa (Barsalou, 2016; Mahon, 2015). However, there is disagreement on whether activation of "sensory-motor" cortex, broadly construed, indicates that sensory/motor representations are recruited *and* play a causal role in behavior. Alternatively, the content of the concepts may be amodal. Thus, sensory/motor processing may be mandatory during conceptual processing (grounded cognition), or may be optional, allowing cognitive processes to operate over purely amodal representations in a "stand alone" manner from modal representations (abstractionism). As such, any sensory/motor activity during conceptual processing may be epiphenomenal.

Letter processing presents a compelling domain in which to examine these issues, given certain empirical findings that are seemingly consistent with the predictions of grounded cognition: sensory/motor cortex activates during letter perception, this activation arises only as result of writing experience, and writing experience is associated with better behavioral performance on letter processing tasks compared to non-motor learning experiences. However, the mere fact that these findings are *consistent* with grounded cognition is insufficient to dismiss the abstractionist position. In this regard it is key to demonstrate that it is aspects of the motor learning *per se*, and not other differences between writing experience and other learning experiences, that form the basis of the observed pattern of results.

The outline of the dissertation is as follows: Chapter 1 elaborates on the background briefly presented in this Introduction, to understand what is and is not currently known about the role of motor experience in perception generally, and in particular the role of writing experience for written language acquisition. This survey of the literature portrays a state of knowledge that is highly suggestive that "writing does matter," but presents mixed findings on what tasks writing experience impacts and has little to say about the underlying cognitive mechanisms and representations. In that chapter, the grounded cognition and abstractionist views are clearly defined, with a focus on the aspects of the debate to which this dissertation is relevant. The first chapter concludes by delineating the outstanding issues—what gaps in knowledge are addressed in the research presented here, and most importantly, what hypotheses are tested. The remainder of the dissertation is organized around answering the three major questions that were first presented in this introduction: (1) Are the effects of writing experience due to motor learning *per se*, or to other variables confounded with the writing experience? (2) Does writing experience recruit only sensory/motor representations? (3) Which types of representations, motoric or otherwise, underlie the behavioral benefits of writing experience?

Chapter 2 describes the methods, the experimental designs, and the analytical approaches for both the behavioral and the neuroimaging experiments. Briefly, adult participants with no previous knowledge of Arabic learned 20 letters of that alphabet, through one of three learning conditions: typing, visual study, or writing. Extensive behavioral testing was conducted at multiple time points before, during, and after the participants reached criteria on a letter recognition task. In addition, both pre-training and post-training neuroimaging sessions were administered to detect changes in the neural representations of the letters as a consequence of the different learning conditions. Chapter 3 then presents the results of the behavioral experiments that elucidate the effects of the writing experience compared to the non-motor learning experiences on a range of letter processing tasks. The findings contribute to understanding which of the benefits previously reported in the literature are due to the motor experience *per se*. The behavioral evidence in Chapter 3 is also examined in light of the theory of distinctiveness processing, to present an account to explain why writing experience may be beneficial for learning letters, even if those benefits are not specifically associated with motoric letter representations. Chapter 4 presents the results of behavioral and neuroimaging experiments that reveal the content of the different letter representations that were learned, and how these representations differed as a consequence of the learning conditions. This includes results from both pre-training and post-training time points, for both a behavioral same/different letter judgment task, and a representational similarity analysis (RSA) of neuroimaging data from a task involving viewing Arabic letters during fMRI scanning. The RSA results reveal the neural consequences of learning experiences in terms of: the types of information represented, the neural substrates that support them, and how these depend on learning experience. Moreover, the representational strength is related to individual differences among the participants in terms of performance on letter processing tasks (e.g., their ability to recognize the letters, or to write words), furthering our understanding of how the neural representations relate to task performance and letter learning.

Finally, Chapter 5 presents a general discussion, moving from answering the specific empirical questions to situating the findings in the larger context of the grounded cognition-abstractionism debate. The findings of this dissertation provide evidence about the content of letter representations in the mind/brain, and the relationships between those representations and performance on letter processing tasks. As will be shown, the results provide evidence of amodal representations that represent a challenge for many grounded cognition theories. However, the results also reveal a relationship between writing experience and *learning* this amodal representation, which suggests a critical role for sensory/motor representations *in the learning* of amodal representations. An account of why writing experience might matter is put forth that combines an abstractionist theory of letter representation (Symbolic Letter Identity; Rothlein & Rapp, 2017) with the theory of distinctiveness processing (Hunt, 2013). This account proposes that writing training facilitates learning symbolic letter identities (SLIs) because it requires mapping between different representations of the same letter, and because the act of writing leaves distinctive memory traces that support visual recognition and recall of the letter-shapes. This hypothesis, and other findings of the dissertation, generate a number of testable predictions about the nature of conceptual representations and how they are learned, which are considered as future directions for research.

Chapter 1 – Background

The primary aims of this dissertation are to investigate in depth the role of writing experience on the learning and perception of letters. These aims are operationalized as three questions: (1) Are the effects of writing experience due to motor learning *per se*, or to other variables confounded with the writing experience? (2) Does writing experience recruit only sensory/motor representations? (3) Which types of representations, motoric or otherwise, underlie the behavioral benefits of writing experience? These questions are addressed through a longitudinal training study of adults learning letters of the Arabic alphabet through different learning experiences (i.e., performing different tasks during study sessions). A number of behavioral and neuroimaging assessments, conducted at multiple time points during the training study, are used in combination to provide detailed information about how learning experience, and in particular writing experience, affects behavioral performance and letter perception. This contributes to our understanding of the nature of conceptual representations in the mind/brain, and in particular the status of amodal representations. It therefore has bearing on the debate, between grounded cognition and abstractionist theories of mind, over whether amodal representations exist, and if so, how they interact with sensory/motor representations.

This chapter begins by further explicating the concepts put forward in the Introduction. The first sections provide more details from the literature on the role of motor experience in learning in general (I. "Effects of Motor Experience on Perception"), and the role of writing experience in letter learning in particular (II. "Previous Findings on the Role of Learning Experience in Letter Acquisition"). This background information is discussed by situating it within the context of the debate between grounded cognition and abstractionist theories, especially with respect to claims about the nature of conceptual representations. The third section discusses what is known about how letters are represented and processed (III. “The Multiple Representations of Letters”), both in behavioral and neural terms.

The second half of this chapter expands upon the outstanding issues that are addressed in this dissertation. It is important to first establish whether the reported effects of writing experience on letter perception can in fact be attributed to the motor experience per se, and not to some other variable(s) associated with the experimental conditions under which participants have performed handwriting tasks. Further arguments about the nature of letter representations and in particular motor representations would be rendered moot if it were found that in fact the critical contributions of writing experience to letter learning does not in fact arise from motor experience *per se*. As such, this section is relevant to the first primary question of the dissertation. Although these issues do not relate specifically to the questions about the nature of conceptual representations, they are important in their own right and have practical implication for understanding how written language is acquired. Therefore, the fourth section presents alternative possibilities that could explain why writing experience benefits letter learning (IV. “Writing Experience Entails More Than Motor Experience”).

The fifth section discusses possible explanations for how writing experience could affect letter learning that would *not* be due to incidental variables. As such, it specifies gaps in the existing body of knowledge and explains how they are addressed in the experiments conducted here (“V. Addressing Outstanding Issues”). Without addressing these gaps, it would be impossible to answer the second and third primary questions. Finally,, the last section makes explicit how the results of this dissertation inform the grounded cognition-abstractionism debate, and in particular our understanding of how conceptual letter representations are learned (VI. “Informing an Account of Learning Letter Representations”). The overarching goal of this chapter is to clearly delineate the issues that are at stake, and to explain how this dissertation informs those issues (full details on the methods and analyses are presented in Chapter 2).

I. Effects of Motor Experience on Perception

Long-standing questions in cognitive psychology ask about the relationship between action and perception in human cognition (Beilock et al., 2008; Brooks & Goldin-Meadow, 2015; Congdon, Novack, & Goldin-Meadow, 2016; Goldin-Meadow, 1999; Kandel, Orliaguet, & Boë, 2000; Knoblich & Flach, 2003; Knoblich & Prinz, 2001; Knoblich, Seigerschmidt, Flach, & Prinz, 2002; McNeill, 1992, 2008; Rauscher, Krauss, & Chen, 1996; Viviani, Baud-Bovy, & Redolfi, 1997; Viviani & Stucchi, 1992). One line of research investigates how knowledge of how an action is performed influences perception of events or of the static traces left as a consequence of those actions (see Knoblich & Flach, 2003 for a review). For example, Casile & Giese (2006) demonstrated that individuals are significantly better at visually recognizing gait patterns corresponding to novel motor actions if they themselves have learned how to perform those actions (Casile & Giese, 2006). In that experiment, participants were taught how to perform new actions while blindfolded, based on verbal instruction and haptic feedback alone, and were subsequently tested on their ability to discriminate between moving dot displays of biological motion. The results of this study are particularly important because they distinguished *visual* experience of actions from *motor* experience (i.e., the participants had no experience with viewing the actions conducted by themselves or anyone else), thereby demonstrating a contribution of motoric knowledge to visual perception, at least in the domain of action perception . A similar finding shows an effect of the amount of real-life experience with performing specific actions, not on visual perception of the actions themselves, but on the brain's response to reading words describing those actions. For example, those who had actually played hockey showed differential brain activation in somatosensory regions when reading sentences like "The hockey player finished the stride," compared to those who had never played hockey (Beilock et al., 2008). In fact, reading action verbs more generally has been found to activate somatosensory cortex (such as leg-related words like "kick" activating somatosensory regions associated with the leg, Pulvermüller, 2005)

In the domain of letter processing, analogous evidence has been reported suggesting that knowledge of how letters are written affects letter perception. There are two types of results: behavioral ones, showing that writing knowledge affects letter recognition, and neural ones, showing that sensory/motor cortex activates during letter perception. In terms of behavioral results, Freyd and colleagues (Freyd, 1983; Freyd, 1987; Babcock & Freyd, 1988) provided some of the earliest indications that dynamic visual information is extracted from the perception of single static letters. For example, they demonstrated that individuals were better able to recognize pseudo-letters if the static visual traces of how they were produced (i.e., varying line thickness and stray marks) were consistent with how they had been taught to produce them, compared to letter-shapes that indicated an alternative motor plan in terms of the direction and/or order of strokes (Babcock & Freyd, 1988). In another study (Knoblich & Prinz, 2001), participants copied letters, both familiar Roman letters and unfamiliar letters from other scripts, without viewing the results of their writing, and were then shown kinematic displays of the letters drawn either by themselves or by others. They were successful in discriminating between the letters they had drawn themselves and those drawn by others based on dynamic visual information alone (i.e., moving dot patterns that left no static trace). In a similar study (Knoblich et al., 2002), participants were asked to judge whether a single stroke had been written in isolation or as part of a larger symbol. While participants were significantly above chance in correctly identifying strokes which they had generated themselves a week prior, they were at chance in identifying strokes generated by others. Recent neuropsychological evidence (Schubert, Reilhac, & McCloskey, 2018) has revealed that dynamic information (i.e., animated displays of letters, as opposed to static images of letters) improved recognition in a patient with a letter identification deficit, but only if that dynamic information was consistent with typical motor plans for writing the letters. Finally, results obtained by Kandel and colleagues (Chary et al., 2004; Kandel, Orliaguet, & Boë, 2000; Kandel, Orliaguet, & Viviani, 2000; Orliaguet, Kandel, & Boë, 1997) demonstrate that the hand movements in writing are anticipated and generate predictions regarding the word that is being written, which suggests that dynamic information may be useful not only for identifying single letters but also entire words.

In terms of neuroimaging results, several studies have reported that even during passive viewing of single letters (Longcamp et al., 2003, 2011, 2014; Longcamp et al., 2006), sensory/motor cortices activate in a way analogous to the activation in primary somatosensory and motor areas during reading of action verbs (e.g., Pulvermüller, 2005). This pattern of activation, which includes brain regions associated with motor planning of the hand used for writing (e.g., "Exner's area", Roux et al., 2009), has furthermore been seen to depend on previous experience with writing letters (see section II of this chapter).

Taken together, the behavioral and neural results all imply that knowledge typically learned only through handwriting experience is recruited during visual letter recognition processes. This conclusion is also supported by evidence that letter identification is disrupted under conditions of motor interference (James & Gauthier, 2009): individuals are less accurate in identifying letters when they are simultaneously drawing similar shapes or letters, compared to dissimilar ones (e.g., poorer identification of curvy letters like C and S when writing curvy shapes versus when writing straight line shapes like L and T). These types of results have been seized upon by proponents of grounded cognition as evidence in favor of their theory. However, it has not been ruled out in any of these cases that there is concomitant causal activation of *amodal* conceptual representations (see section III "The Multiple Representations of Letters").

II. Previous Findings on the Role of Learning Experience in Letter Acquisition

Questions about the importance of handwriting for learning to read have been of increasing interest to researchers, teachers, and parents since the proliferation of computers and the decline of the teaching of penmanship in many school curricula. From the education perspective, teachers and parents alike have wondered whether this sea change in written language production is having an impact on the ability of students to successfully learn not only to write, but also to read. Furthermore, findings such as those of Berninger and colleagues (Berninger, Abbott, et al., 2006; Berninger, Winn, et al., 2006; Richards et al., 2011) have been generally supportive of a role of motor experience in literacy acquisition, reporting correlations between measures of language development (e.g. reading ability, vocabulary) and both handwriting and typing skills, and that, on balance, young children (grades 1-6) are more productive in written output when writing by hand than typing on a keyboard. Relatedly, there are results reporting that handwriting compared to typing of classroom notes leads to better retention of information (Mueller & Oppenheimer, 2014; Ouellette & Tims, 2014). However, this avenue of research is generally more focused on the ability to translate language and thought into meaningful sentences and paragraphs, and *not* on more basic cognitive processes such as those that that underlie the ability to spell single words or identify individual letters. This dissertation focuses on the latter aspects of written language.

Another reason why letter recognition may be likely to be influenced by writing experience is because, as has often been noted, reading and writing are typically acquired in tandem. Moreover, handwriting or other motor experience with letters has long been a popular remedy for children showing difficulties learning to read (Bara & Bonneton-Botté, 2018, 2018; Fernald & Keller, 1921; Orton, 1928). While these findings are suggestive of the possibility that memories of how letters are written aid visual letter recognition, more direct evidence comes from studies that have manipulated the conditions under which letters are learned.

At least 19 articles have been published in which individuals were taught letters via different learning experiences, with the explicit aim of comparing the effectiveness of writing experiences to others (see Bhide, 2018, for a review of the most relevant behavioral findings). This has included both children and adult learners, and both between- and within-participant designs. The learning experiences have included different types of motor activity:

tracing, copying, and writing (the distinction between the latter two being that copying is done with the stimulus present while writing is done from memory). Several studies have included a typing condition, invariably referring to this condition as a motor experience. However, as will be argued in subsequent chapters, typing is probably best thought of as a type of visual experience. This is particularly so in the studies with children, or adults learning a second language, because the typing activity is slow and laborious (a visual search, in fact), and not automatized touch-typing. Most studies also include a “purely” visual learning experience, wherein no overt responses at all are made during the study sessions. In order to determine whether motor experience has different effects on the outcomes of learning compared to non-motor experiences, researchers have collected both behavioral and neuroimaging measures (fMRI). The studies that have reported significant effects of learning experience on neural activation, have either failed to test behavior, or have done so, but reported null results.. In other words, no study has reported any associations between neural activity during letter processing and behavior, either in terms of individuals differences or groups (e.g., comparing those with writing experience to those without). As for the significant findings of behavioral differences between motor and non-motor learning experiences, overall the results have been very mixed. Generally, motor experience has been found to be superior to other learning experiences, but this is affected by the nature of the motor experience, the other conditions to which it is compared, and what skills have been assessed as outcome measures. The following paragraphs discuss these findings, both neural and behavioral, in greater detail.

Cognitive Neuroscience Findings

A number of neuroimaging studies have investigated whether the patterns of neural activity generated during viewing or producing learned letter shapes are affected by the characteristics of an individual's learning experience. Several studies have found that the pattern of brain activation while reading letters depends on the person's previous experience producing them (James, 2010; James & Atwood, 2009; James & Engelhardt, 2012; Kersey & James, 2013; Vinci-Booher, James, & James., 2016). James and Engelhardt (2012) provide the clearest support for the notion that the typical adult *reading circuit* (the pattern of activation expected of an average adult when performing reading tasks) arises after learning to write letters by hand, as opposed to learning to type or trace them. This reading circuit includes both the visual word form area (Dehaene et al., 2002; McCandliss, Cohen, & Dehaene, 2003), an area of the left fusiform gyrus held to be a key region of the reading circuit, and an extended network of other regions believed to be recruited during reading, Specifically, in a within-participants manipulation, they taught children to produce letters by handwriting, typing, and tracing, and found that children demonstrated activation in the adult reading circuit regions during passive viewing of letters, but only if they had written those letters by hand. A similar result was found among adults trained on pseudoletters (James & Atwood, 2009) either by writing, typing, or visual study. During scanning, the participants were then shown both the pseudoletters they were trained on and untrained pseudoletters, and the results revealed stronger activation for learned letters relative to novel ones, in the left fusiform and dorsal precentral gyrus, but only for letters that had been practiced by handwriting.

More recent work by James and colleagues (Vinci-Booher, James, & James, 2016) made use of functional connectivity analysis to posit a mechanism by which handwriting might lead to effects on letter perception. Specifically, in a reanalysis of the data of James & Engelhardt (2012), only handwriting experience and not typing or tracing led to strengthened functional connections during passive viewing of letters between the left fusiform gyrus and left dorsal precentral and postcentral gyri. While the left fusiform is implicated in word reading and spelling, the left dorsal pre- and postcentral gyri are associated with primary motor and somatosensory functions—increased connectivity between these regions is *consistent* with the account put forward by those authors: that handwriting uniquely (compared to typing or tracing) requires integration of fine motor skills with proprioceptive and visual feedback. This is supported by the findings that inconsistent proprioceptive feedback interferes with letter identification (James & Gauthier, 2009). Taken together, these results suggest that handwriting may be uniquely well-suited to strengthening the connections in the brain involved in motor/proprioceptive feedback that may contribute to visual processing. Finding that typing experience does not lead to the same behavioral benefits as handwriting experience is thus explained by the fact that typing skills do not require knowledge specific to the geometry of the letter shapes (as the mapping between letter-shapes and keyboard locations is arbitrary). Thus, typing experience would not foster strengthening connections between motor and visual processing areas in the same way as handwriting experience.

A major caveat to all of the aforementioned neuroscience findings is that they have been observed in the absence of behavioral effects of motor experiences/training. That is, the results just discussed that show effects of the type of learning experience on neural activity looked for, but did not find, behavioral benefits of writing experience on letter processing tasks (James, 2010; James & Atwood, 2009; James & Engelhardt, 2012; Kersey &

James, 2013; Vinci-Booher, James, & James, 2016). The evidence that writing experience is more beneficial for letter learning than non-motor experiences comes from a separate set of studies focused on the behavioral and not the neural consequences of learning experience.

Behavioral Findings

While neuroimaging studies have reported neural consequences of different experiences in training with letters or pseudoletters, behavioral studies have not consistently found differences in learning outcomes between handwriting and typing training (Bhide, 2018; Guan, Liu, Chan, Ye, & Perfetti, 2011; James & Atwood, 2009; James & Engelhardt, 2012; Kersey & James, 2013; J. X. Li & James, 2016; Longcamp, Boucard, et al., 2006; Longcamp et al., 2005; Naka, 1998; Naka & Naoi, 1995; Vinci-Booher & James, 2016; Zemlock et al., 2018). A few researchers (Guan et al., 2011; Naka, 1998; Naka & Naoi, 1995) have found that learning new shapes only by visual memorization results in poorer learning compared to learning by handwriting. In addition, two studies have reported differences in learning outcomes when learning experiences involving handwriting vs. typing are compared (Longcamp, Boucard, et al., 2006; Longcamp et al., 2005). Specifically, Longcamp and colleagues (Longcamp et al., 2005) demonstrated that children (mean age 46 months) trained to either type or write unfamiliar Roman letters were significantly more accurate in identifying the letters (in arrays that included three non-letters) that they learned through writing compared to typing. It was also found that adults who were trained to either type or write Gujarati characters (Longcamp, Boucard, et al., 2006) were significantly better at discriminating previously learned shapes from left-right reversals, for those characters learned via writing versus typing. However, several other studies have reported no significant differences in *learning* outcomes across learning experiences (e.g., typing or writing), including the studies of James and colleagues that reported differences in *neural* outcomes (James, 2010; James & Atwood, 2009; James & Engelhardt, 2012; Kersey & James, 2013; S. Vinci-Booher et al., 2016). This is particularly problematic for arguments that handwriting instruction should be part of classroom education. Furthermore, it raises the possibility that the neural findings that have been reported are unrelated to any behavioral benefits that have been reported. However, alternatively, it could be argued that the neural measures were more sensitive than the behavioral measures (accuracy and RT), either because behavioral changes sometimes lag behind neural changes (the argument put forth in James, 2017), or because the behavioral tasks were inadequate for detecting the behavioral changes (e.g. ceiling or floor performance).

Ultimately, five shortcomings can be identified in the literature investigating the impact of motor/non-motor experience on letter learning: (1) inadequate training of participants and assessment of learning, (2) low educational relevance (low "ecological validity") of assessments, (3) failure to account for confounds between the type learning experience and irrelevant demands of the training task, (4) insufficient assessment of long-term retention, and (5) absence of investigation of the nature of the learned letter representations. Each of these shortcomings is explained further (Section V. "Addressing Outstanding Issues"), and are specifically addressed in this dissertation (see Chapter 2). The overarching goal is to better understand the nature of letter representations in the mind/brain, how they are affected by learning experience, and thus the extent to which the role of writing experience on letter learning supports theories of grounded cognition or abstractionism. It should be noted that none of the studies just discussed, either behavioral or neural, investigated the nature of the underlying letter representations. Therefore, the next section reviews what is known about the contents of letter representations.

III. The Multiple Representations of Letters

The study of letter perception dates back to the earliest days of experimental psychology (Cattell, 1886; Javal, 1881), due both to their critical role in reading and writing of alphabetic languages, and also because they present unique opportunities for understanding visual object perception in general. Traditionally, the focus of investigation has been specifically on understanding the ability of the visual system to recognize letters. More recently, researchers have investigated questions relate to other types of letter representations: phonological (letter names and the phonemes they represent), motoric (the shape, direction, and sequence of strokes for writing letters), and orthographic. This last category is particularly relevant to the grounded versus abstract cognition debate, because proposed orthographic representations are *amodal* in nature. These include representations of letter position, letter case, and symbolic letter identities (SLI)—all properties of letters that are either unobservable in specific modalities or cut across the modalities, as in the case of SLI (e.g., the letter name /ei/ and shapes “A” and “a” all correspond to the SLI [A]). Thus, any evidence that these concepts have amodal representations, with instantiations in the brain and/or underlie behavioral effects on letter processing tasks, is problematic for grounded cognition views that reject amodal representations.

Evidence for these different types of letter representations has come from both behavioral and neural experimentation. In this section, the findings providing understanding of these different representations are summarized, and a cognitive architecture is presented for an existing abstractionist proposal of how the amodal representation of SLI mediates between the different modality-specific representations.

The Contents of Letter Representations

Perhaps the most obvious type of letter information is visual. The leading theory of visual letter processing currently is that letters are recognized via their component visual features (Changizi, Zhang, Ye, & Shimojo, 2006; Courrieu, Farioli, & Grainger, 2004; Gervais, Harvey, & Roberts, 1984; Grainger, Rey, & Dufau, 2008; Wiley et al., 2016), as opposed to template-matching processes that attempt to recognize exemplars by comparing them to prototypical letter-shapes (for an overview see Palmer, 1999). Active research focuses on identifying the precise nature of those visual features is (Fiset et al., 2009, 2008; Wiley et al., 2016). Other lines of research have investigated the importance of not only letter-shapes but also letter names in learning to read and spell (Treiman, 2011; Treiman & Kessler, 2004; Treiman, Levin, & Kessler, 2007; Treiman et al., 1998), and several studies have included letter name representations as a factor potentially affecting visual letter perception (Courrieu et al., 2004; Lupyan et al., 2010; S. T. Mueller & Weidemann, 2012; Rothlein & Rapp, 2014, 2017; Wiley et al., 2016).

For visual and phonological letter representations, both empirical and theoretical measures have been used to quantify the similarity of letters along those dimensions. For example, the similarity of visual representations can be indexed by low-level similarity measured in terms of the proportion of overlapping pixels, by observed rates of visual confusion errors (typically under limited viewing conditions such as brief exposure, or else by naïve observers like children), or by measuring the proportion of theoretically posited shared visual features (such as lines, curves, and intersections). The similarity of phonological representations has been indexed by both observed confusion error rates in auditory recognition of letter names or by measuring the proportion of shared phonological features of the letter names (e.g., voicing, place of articulation, etc.).

Relatively less is known about the content of motoric representations of letters. One particular challenge with motoric representations is the difficulty of distinguishing motor features from visual features, given that there is necessarily a high correlation. For example, a vertical line in a letter is necessarily the result of a vertical stroke. However, some evidence indicates that the two dissociate, providing information about the content of motoric representations. For example, there is neuropsychological evidence from individuals with acquired dysgraphia that, subsequent to a stroke, letter substitution errors may be based on the similarity of letters' strokes, and not their visuospatial characteristics (Rapp & Caramazza, 1997). Importantly, the proposed motor stroke features in that study took into account the *direction* of strokes—thus for example, both a downward and an upward stroke will produce a vertical line, allowing for a differentiation between a letter-shape such as T (downward stroke) and N (upward stroke) in terms of the motor representation, but not the visual representation. Wiley, Wilson, & Rapp (2016) provided behavioral evidence that visual same/different letter judgments are influenced by the similarity of letters' motor representations, using a metric that not only included direction of strokes but also stroke sequence. Wiley et al. found that the motoric similarity of letters made unique contributions to explaining both reaction time and accuracy in the visual same/different task, even controlling for visual similarity.

While visual, phonological and motoric letter representations are entirely consistent with grounded cognition theories, there is at least one type of letter representation that is not related to a sensory modality but which nonetheless also has empirical support. This is the amodal representation of symbolic letter identity (SLI), which is a representation of the concept that allographs, (different letter-shapes that represent the same letter) have the same identity, despite potentially gross differences in their visuospatial and motoric representations; for example, the allographs “a”, “a”, and “A” have the same SLI of [A]. Recent work (Rothlein & Rapp, 2014) identified a region of the brain spanning the parahippocampal and mid-fusiform gyri as being selectively sensitive to SLI. Specifically, it was found that only this region of the brain has a similar neural response to different inputs (such as lowercase “a” and uppercase “A”) regardless of their visual or motoric similarity, and also was shown not to reflect phonological (letter name) similarity. The identification of this brain region substantiates claims of the existence of SLIs. This claim is based on representational similarity analysis (RSA), an approach to analyzing neuroimaging data that is especially well suited to addressing questions about representational formats. RSA is a technique for quantitatively comparing the similarity of neural representations of stimuli (within a given set of voxels) to a model of their similarity for a specific type of cognitive representation (e.g., visual similarity). In other words, RSA allows one to infer representational content of neural representations by evaluating the degree to which the similarity of neural responses matches the similarity along the representational dimension of interest . The evidence for SLI in Rothlein & Rapp (2014) thus comes from the finding that this part of ventral-occipital temporal cortex shows the patterns of cross-voxel neural response similarity that are predicted if cross-case letter pairs are represented as identical (e.g. "A" and "a"), without showing sensitivity to similarity on modality-specific dimensions: phonological, visuospatial, or motor.

This evidence is problematic for views that deny the existence of amodal representations, and in particular for embodied cognition, which assumes that all letter representations are sensory/motor representations: predicting, for example, that the letter-shapes "a" and "A" should generate similar neural representations only to the extent that they share physical properties. The most obvious way for these two different letter-shapes to be treated identically under an embodied account is via their identical letter names. However, not only did the analysis supporting the neural evidence for SLI (Rothlein & Rapp, 2014) take this possibility into consideration, there is also a wealth of behavioral evidence of letter identity effects that cannot be explained by letter names. These findings come primarily from cross-case matching tasks (e.g., match "a" with "A" and "b" with "B") and the same/different judgment task (see Schubert, Gawthrop, & Kinoshita, 2018), and has been found for Roman letters, Arabic letters, and even an equivalent concept for Japanese kana and the behavioral evidence (e.g., Carrasco, Kinchla, & Figueroa, 1988; Norris & Kinoshita, 2008; Rothlein & Rapp, 2017; Schubert, Gawthrop, & Kinoshita., 2018; Wiley, Wilson, & Rapp, 2016). What these studies all show is that, during perceptual tasks, allographs are responded to more similarly than non-allographs, whereas letters with similar names are *not* responded to more similarly. For example, "b" and "B" will be responded to more similarly than "b" and "p", because of their shared identity, whereas "b" and "p" are *not* responded to more similarly than "b" and "q", despite the much more similar letter names.

Letter Representations in the Grounded/Abstract Cognition Debate

The difference between abstractionist views, which posit the existence of amodal representations for concepts like SLI, and the embodied cognition view that denies any amodal representation, is clarified in Figure 1-1 (taken from Rothlein & Rapp, 2017). According to this proposal, SLI plays a key role in "mediat[ing] translation between modality-specific formats" (Rothlein & Rapp 2014, 322). For example, reading the letter string XGZ as "ex gee zee" is achieved by accessing the SLI [X], [G], and [Z] from the visual representations and linking those SLIs to phonological letter name representations.. This is in contrast to an embodied cognition account, wherein such a task must be completed without appealing to an amodal representation of SLI—this is achieved by past association of information represented in different modalities, such as by transcoding the visual representations directly into the letter names. Embodied accounts are challenged to explain what the representational content of the putative SLI-sensitive brain region found in Rothlein & Rapp is, if not an amodal symbolic representation, as well as to show that apparent SLI effects on cross-case matching tasks and same/different judgments are in fact due to direct associations between modality-specific representations (such as letter names).

Unlike strong embodied cognition views, however, grounded cognition is generally less restrictive regarding the types of representations that may exist, allowing that visually dissimilar allographs like "a" and "A" can have a common conceptual representation, to the degree that they have been experienced and interacted with as equivalent objects in the environment ("interactions among action-environment-perception", James, 2017). There are at least two proposed mechanisms for how abstract concepts like SLI can have representations that are not necessarily amodal. The first has been termed "distilled abstraction" (e.g., Jamrozik et al., 2016; Barsalou et al., 2016), which proposes that concrete features are stripped away until only abstract ones are left behind. This could be achieved by processes of metaphor. For example, the SLI concept is akin to the metaphor "A" = "a". The abstract features that afford such metaphors are proposed to be "distilled" by stripping away concrete features. Thus, in order for "A" = "a" to be true, information about differences in the physical shapes of the two letters must be removed from their representations. Ultimately, the distillation processes leaves behind only information that is consistent with the abstract concept. Because this process not only begins with sensory/motor representations, but also allows for representations that still retain *some* modality-specific information, it is considered to be consistent with grounded cognition theory.

A second, similar proposed mechanism for constructing abstract representations has been termed "multimodal compression" (e.g., Barsalou, 2016; Binder, 2016). In multimodal compression, information from multiple modalities increasingly converges, compressing details about different specific modalities together into representations that represent only partial information about any single modality. Multimodal compression is thought to be supported by "association areas" in the brain, which integrate information from sensory/motor areas in a hierarchical fashion in order to representation abstractions. Both the distilled abstraction process and this multimodal compression process *could* result in amodal symbols, given a sufficient amount of processing such that no modality-specific information remains retrievable (Binder, 2016)—in other words, in the limit, representations could become amodal. However, the representations arising from multimodal compression are considered to be representational prototypes (Barsalou, 2016), and importantly, "prototypes are not amodal symbols arbitrarily linked to exemplars. Instead, the features of exemplars appear in the prototype that covers exemplars," (1133, Barsalou, 2016).

The discussion of these two mechanisms, distilled abstraction and multimodal compression, underscore a critical distinction between grounded and abstract cognition theories. It is not the case that all proponents of grounded cognition absolutely refute the possibility of amodal symbols. Some, but by no means all, grant that amodal symbols may be needed to represent information that truly cuts across multiple modalities, such as space or magnitude (see e.g., Barsalou, 2016; Braga, Wilson, Sharp, Wise, & Leech, 2013). However, grounded cognition theories by definition require that all concepts ultimately have some means of grounding them to the modalities. Mechanisms such as distilled abstraction and multimodal compression predict that fundamentally, even amodal features like magnitude depend on modality information, because they depend on processing streams that do represent modality-specific information. This stands in clear opposition to all abstractionist views, which have in common not only that amodal representations exist, but that they do *not* fundamentally rely on modal representations[4].

Many of the previously mentioned studies that provide evidence of an amodal SLI representation do also report effects arising from sensory/motor representations, and

[4] It may be that abstractionist views would grant some reliance or contribution of modality-specific information during the learning of amodal representations, in particular ones corresponding to concrete concepts like color. The question of how amodal concepts are *learned* is returned to in the final discussion (Chapter 5).

certainly more information is needed to adjudicate between grounded cognition and abstractionist theories. This dissertation strengthens the evidence for both sensory/motor and amodal letter representations of letters in two ways. First, it provides evidence that amodal representations are not unique to the Roman alphabet, nor limited to case-specific allographs. While Arabic also has allographs, they have historically arisen for a different purpose, which is to represent the letter's position within sub-words, and thus the orthotactics that determine their usage are different from those determining the use of lowercase or uppercase Roman letters. Second, because this study manipulates the learning experiences that individuals have, it allows for developing a theory of how letter representations, amodal or otherwise, are *learned*. For example, differences in motoric representations across learning experiences can be directly attributed to the writing experience (or the lack thereof). Moreover, thus far no study on the effects of motor experience on letter learning has included allograph stimuli, and thus the concept of SLI has not been testable in this context. This allows for a stronger test of the grounded cognition hypothesis that the benefits of writing experience for letter learning is due to motoric representations, and that activation in those associated areas reflects sensory/motor representations and not amodal, SLI representations.

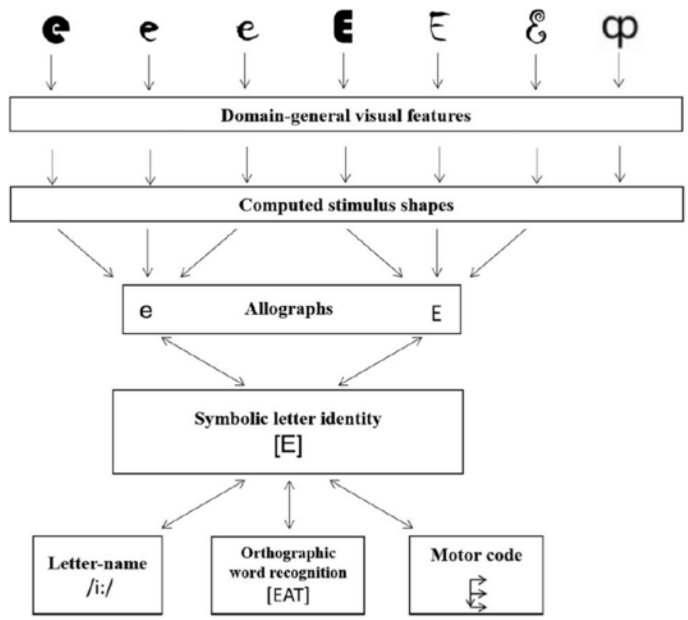

Figure 1-1. From Rothlein & Rapp, 2017 (Figure 1, 1412). Symbolic letter identities serve as mediators between visual forms, letter names, word forms, motor codes, etc.

IV. Writing Experience Entails More than Motor Experience

While there is evidence that motoric letter representations affect behavior on perceptual tasks (see section III. "The Multiple Representations of Letters"), there is not yet any evidence that motoric representations themselves play any role in how well letters are learned. In that regard it is important (though not sufficient) to establish that at least some of the reported effects of writing experience are attributable to the motor experience per se, and not to some other variable(s) associated with the experimental conditions under which participants have performed handwriting tasks. This section highlights five possible sources of behavioral effects that arise only indirectly and circumstantially through the conditions under which writing experience is gained. Some of these have been previously discussed in the letter learning research, while others have been posited to explain similar effects in domains other than letter learning, but are equally relevant in this context.

Consideration of these five possible sources of behavioral effects may shed light on the mechanism, or mechanisms, underlying the role of motor experience in learning letters and in letter processing more generally. Only one of these has explicitly been discussed in relation to the role of motor experience and letter perception. The others derive from research on human learning and memory, including both fundamental properties of human memory and research on false memory (Schacter, Israel, & Racine, 1999). Some of these have been proposed to explain the mechanism(s) underlying the production and generation effects, some of which have been ruled out (see Bertsch et al., 2007; Bodner & MacLeod, 2016 for reviews). Each of the five are presented here, and connections are made between their original context and their application to the specific domain of writing experience and letter perception.

(1) Variable Visual Input

The possibility has been raised that the apparent effects of writing experience on letter learning are actually due to the fact that the output of handwriting is variable letter exemplars, and that subsequent viewing of these variable shapes “may serve to broaden perceptual categories, and in turn, enhance visual processing of that stimulus class” (page 11, Kersey & James, 2013; see also James & Atwood, 2009; James & Engelhardt, 2012). This hypothesis was put to the test by Li & James (Li & James, 2016), in a between-participants experiment where children learned Greek letters by either writing, tracing, or visual study. In order to adjudicate between the effects of motor experience and the viewing of variable exemplars, participants were either trained on exemplars of a single, typed font or were given variable exemplars (i.e., during study they were exposed to multiple typed fonts, or to variable exemplars created by sampling from other children's handwritten productions). A symbol categorization task was administered as a post-test, wherein participants were given novel exemplars (both typed fonts and handwritten exemplars they had not previously seen) and were asked to sort them into 5 piles, one for each of the 4 Greek letters they had learned and one reject pile. The most important finding was that those that had learned the Greek letters by either tracing or visual study of a single font (i.e., zero variability of input) performed significantly worse than those who had learned by handwriting or by tracing or visual study of variable exemplars. There were no differences in performance between those who had learned by handwriting and those who learned by tracing or visual study of variable exemplars. On the basis of this result, the authors concluded that the critical aspect of writing experience is actually results from observing the variable output of handwriting, supporting "the notion that category learning is facilitated by exposure to multiple, variable exemplars" (page 309, Li & James, 2016).

This conclusion rests on the result from the card sorting task, but is premature, given that the significant result was driven entirely by differences in the rates of *rejecting* novel exemplars in the card sorting task, not of incorrect categorization. It is important to consider what cognitive processes are necessary for this card sorting task—presumably it entails comparing the novel exemplars to the prototype exemplar (i.e., the piles into which cards were to be sorted were labeled with a target exemplar), and either accepting the novel exemplar as sufficiently visually similar, or rejecting it as too dissimilar from any of the prototypes. Therefore, the "failure" of the children trained in zero variability of input conditions could simply be due to having a higher threshold/narrower understanding for what constitutes an acceptable exemplar. While this may be an interesting finding, it ultimately answers only a much narrower question: is it the motor aspect of writing experience or variable input *that affects the construction of the visual letter categories*. While certainly a part of learning to recognize letters is to develop a concept of what constitutes an exemplar of one letter versus another, this is only a part of the overall concept of a letter. Moreover, it is (by definition) a component of the *visual* representation of letters, and thus it is particularly unsurprising that variable input is a key factor. In other words, it is not surprising that previous exposure to only one specific exemplar of a shape would result in a more restricted concept of what that shape is. The original impetus behind the variable input hypothesis were findings about letter recognition, categorization, and retention, but the way that the card sorting task was conducted in Li & James (2016) fails to address these findings, because they did not examine performance on these tasks[5]. As such, it remains to be tested whether variable input accounts for the wider array of effects of writing experience on letter learning.

(2) An Effort Account

[5] Although the card sorting task might seem to be relevant to the skill of "letter categorization", giving the participants the option of rejecting the letters left open the possibility that those who learned the Greek letters with zero variability of input might have correctly categorized the novel exemplars, had they been forced to choose from among the 4 possibilities. In other words, it demonstrates only that they have a more narrowly-defined visual category, and not that they couldn't recognize the rejected exemplars, such as in the context of a word. As for testing letter recognition, a 4 alternative forced choice test administered in Li & James (2016) found the second-highest accuracy among participants in the visual study, zero variability of input condition—therefore, the evidence was not consistent with the variable visual input account. No measures of retention were obtained.

The effort account posits that generating or producing an item requires more effort than simply studying it, and thus the benefit of writing experience reduces to the greater effort required compared to other learning experiences like typing or visual study. This account is akin to concerns that have been expressed in the letter learning literature about "time on task", i.e., that participants writing letters may perform better not because of writing *per se* but because there is more time and/or attention spent studying the letters under these conditions. While an effort account is appealing, there are two challenges: first, a *purely* effort-based account is challenged to explain results indicating that seemingly easier conditions lead to larger benefits (Bertsch et al., 2007), and second and perhaps more importantly, "effort" is too vague a notion to satisfyingly explain generation/production effects.

(3) Selective Rehearsal Displacement

This explanation was first suggested for the generation effect[6] (Slamecka & Graf, 1978), and proposes that generated or produced items are favored over items that have not been generated/produced, because they receive more attentional resources and therefore result in stronger memories (for a review, see Bertsch et al., 2007). This theory has received some support from the fact that, in certain conditions, it has been shown that part of the apparent

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[6] The generation and production effects were described in the Introduction. Briefly, the generation effect refers to findings that self-generated items are better remembered relative to items that are given (e.g., better memory for the word "kitten" if it was generated based on a cue, such as "what means a young cat and rhymes with mitten?", then if it was simply presented). In a similar way, the production effect finding is that producing the to-be-remembered items leads to better subsequent recognition and recall (e.g., writing the word "kitten" by hand rather than simply reading it).

benefit for generated/produced items is in fact due to a *cost* (selective rehearsal displacement) for the other items: in mixed-list designs where some items are generated/produced and some are not, there are lower rates of recall for the non-generated/produced items than would be expected had they been studied in pure-lists where no items were generated/produced. Applied to the studies of the role of writing experience in letter learning, if the writing experience is given as a within-participant manipulation, then the selective rehearsal displacement account predicts that letters learned via writing practice are only recalled better relative to letters learned by other conditions such as visual study. However, this cannot account for the effect of writing experience in between-participant designs, and so can be rejected as a general explanation.

The selective rehearsal displacement hypothesis is based on a more general phenomenon, which is that of the very straight-forward "stronger memory" account (Bodner & Taikh, 2012). Based on general principles of human learning and memory, a stronger memory account simply claims that memory traces are strengthened by repetition (Murdock, 1989; Ozubko & MacLeod, 2010), and thus seemingly complex phenomena like the production effect, or the benefit of writing experience for learning letters, may be due to learning conditions that resulted in more repetition. This is relevant to the letter learning literature because, as was pointed out in discussion of the variable visual input account, writing results in viewing two exemplars on each study trial: once when viewing the prompt, and once when viewing the self-generated exemplar. In addition, writing letters typically takes more time than non-motor learning conditions, especially compared to most visual study conditions, and so in between-participant designs, the writing condition may simply involve a greater amount of exposure to the visual exemplars. For the most part, previous studies have conducted *post hoc* analyses to demonstrate that behavioral outcomes of learning letters do not correlate significantly with the amount of time spent on task (but see Zemlock et al., 2018, for one attempt to equate the amount of time spent in writing versus visual study), but this an aspect of experimental design that certainly could be improved upon.

(4) Transfer-appropriate Processing

In the research on generation and production effects, it has been pointed out that certain tasks used during study may allow participants to rehearse skills that are more similar to those required by the tasks used to measure learning (Bertsch et al., 2007). In other words, the observed benefits of certain learning conditions may be due to a closer match between the assessment tasks and the learning tasks. An obvious example is if participants who have writing experience are found to produce more well-formed letter-shapes in a writing-to-dictation task, compared to participants who had only visual experience—such a result could be explained by the fact that the writing experience was more readily transferred to a writing-to-dictation task. Of course, finding that writing experience is beneficial because it more readily transfers to other tasks is not the same as finding that it is due to peripheral factors of the writing condition. A transfer-appropriate processing account would be entirely *consistent* with grounded cognition; however, it would not specifically support it without demonstrating that the transfer from writing experience to letter processing tasks is associated with motoric letter representations. As such, a transfer-appropriate processing account would leave unresolved the fundamental issue of determining the nature of letter concepts.

Any learning experience that is beneficial for behavioral performance must necessarily be so because it allows *some* transfer between what was learned during study and what is subsequently tested (i.e., *generalization* of learning). Therefore, transfer-appropriate processing is more a hypothesis that describes the effects of learning experience on letter learning, rather than an explanation. Furthermore, it emphasizes the need to understand how the learning experience affects the content of letter representations. Determining which types of representations are affected by writing experience, and how those representations associated with behavioral performance, is informative both for the grounded/abstract cognition debate, and for understanding the content of representations that are transferred from the learning task to tasks assessing letter processing (see section VI. "Informing Accounts of Conceptual Representations & Letter Learning").

(5) Distinctiveness Processing Account

This account hypothesizes that generation/production is beneficial to the extent that it provides distinctive memory traces, which serve as useful heuristics for recall. Under this account (Forrin, MacLeod, & Ozubko, 2012; MacLeod & Bodner, 2017), episodic memory of the "event" of generating or producing a study item provides an additional cue to recall (i.e., in addition to the memory of having been presented with the item itself). One requirement is that the act of generation or production must be item-specific, or in other words, the acts must be distinguishable from one another. Thus, for example, simply repeating a rote motor response (e.g., pressing a button or saying "next" to proceed to the next trial) while studying each item will not be beneficial, because (a) a rote response does not relate intrinsically to the item, and (b) making the same response to all items cannot serve to differentiate between them. The memories of distinctive acts of production thereby provide additional cues for successful recall.

The theory of distinctive processing (Hunt, 2013; Hunt, Smith, & Dunlap, 2011), first of all, highlights that distinctiveness is not merely difference, but is difference within the context of similarity (von Restorff, 1933). A single picture amongst a list of words is not only distinctive because it is different than the words, but because the words are all relatively more similar to one another in comparison. In the context of writing experience during letter learning, the implication is that it is the distinctiveness of the various learned motoric representations that aids recall, for example in letter recognition tests. Learning by writing is more beneficial than by visual study alone, as that training condition provides no additional cues whatsoever, given that no distinctive responses were produced.

It has further been argued that the distinctiveness heuristic consists of two components that together reduce false alarms. First, it engages output monitoring (Gallo, 2006; Koriat & Goldsmith, 1996; Schacter et al., 1999) in a particular way. In output monitoring, individuals select from among the possible responses that come to their mind, prior to making a final decision. The distinctiveness heuristic account is that individuals are better at rejecting incorrect possible responses by using information about their production (or lack thereof) of those items—essentially, the account goes "I think the answer is A, B, or C, but I only remember *producing* C, so my answer is C". However, it is argued that distinctive processing reduces false alarms not only via improving output monitoring, but also by reducing the set of possible responses that come to mind in the first place ("I think the answer is A or C…", not "A, B, or C"). This process has been termed "event-based distinctive processing" by Hunt and colleagues (Hunt et al., 2011), and is summarized as follows:

> "Perception and comprehension of difference in the context of similarity yield diagnostic information about particular objects and events. Reinstating that processing at test both constrains search, such that access is limited to the target event, and enhances identification and reconstruction of target items within that event." (13, Hunt, 2013)

If the distinctiveness processing account is correct, then writing experience may be beneficial for learning letters because producing the letters leads to better learning of what makes them distinctive from one another, and moreover, this knowledge is used during letter perception, improving the accuracy and speed of letter identification (to the extent that letter identification relies on visual recognition). However, this account also would predict that any other learning condition that provided distinctive production/generation effects would similarly be beneficial. For example, copying letters by constructing them out of pipe cleaners, or performing visual tasks that require constructing the letters out of fragments, would be expected to be beneficial, too. The distinctiveness processing account in that sense, then, suggests that there is nothing unique to the writing experience that benefits letter learning, but rather that it is just one of many possible learning conditions that engage the production effect.

V. Addressing Outstanding Issues

The previous section enumerated accounts regarding how writing experience could affect letter learning *for reasons other than the motoric processes/representations* that are acquired with that experience. Alternatively, the default account is that indeed, writing experience directly leads to developing knowledge that is somehow useful not only for writing itself, but for letter processing tasks more generally. The most popular interpretation of this is an account from grounded cognition—that motoric representations and the neural substrates supporting them are necessarily recruited during letter processing. The implication of this is that only writing experience leads to those motoric representations, and that in turn these representations are directly implicated in behavioral performance.

However, it is possible that writing experience would directly benefit letter learning and processing without being *limited* to effects stemming from motoric representations. This is important because, if writing experience affects learning and perception for reasons not exclusively related to motoric letter representations, then the findings cannot be taken to provide much evidence in support of grounded cognition theories.

This section describes the limitations of previous research that must be overcome in order to provide further insight into the grounded cognition-abstractionism debate, as well as to provide support for implications for educational research. The efforts to overcome these limitations contribute *both* to ruling out the possible explanations of why writing experience might affect letter learning for incidental reasons (as discussed in section IV above), *and* to putting the grounded cognition account to the test. As such, the efforts described below specifically strengthen dissertation's ability to provide evidence addressing the second and third main questions of the dissertation: (2) Does writing experience recruit only sensory/motor representations? (3) Which types of representations, motoric or otherwise, underlie the behavioral benefits of writing experience?

Inadequate Training and Assessment of Learning

The training tasks used have not always required that participants learn to fully identify the letters (i.e., memorize names and shapes and associate the two), but instead have allowed the possibility that the letter learning remains at a superficial level (such as recognizing whether or not a shape is familiar, regardless of whether its identity is known). In terms of learning assessments, the vast majority of studies have asked participants to simply identify which shape is the one they learned out of two options, which shape is the proper form out of four options (with all distractors being non-letters), or categorize various exemplars as tokens of the same type (James, 2010; James & Atwood, 2009; J. X. Li & James, 2016; Longcamp et al., 2005; Zemlock et al., 2018). These assessments all leave open the possibility that only the most basic components of letter recognition have been successfully learned. For example, as depicted in Figure 1-1, given a letter-shape as input, the earliest steps of recognition involve detecting the visual features and computing an overall stimulus shape. A stored memory of the stimulus shape is sufficient for successfully completing these simple letter recognition tasks, and thus such an assessment does not constitute evidence that representations of allographs/identity have been learned, or indeed any information about motor or phonological letter representations. Furthermore, none of the studies have taught the sounds of letters, and thus no learning or assessment of words has been possible. Given the findings that knowledge of letter names and sounds, and not just their shapes, is important for learning to read and write (Berninger, Abbott, et al., 2006; Treiman, Cohen, Mulqueeny, Kessler, & Schechtman, 2007; Treiman & Kessler, 2004; Treiman, Levin, et al., 2007; Treiman et al., 1998), it is important to know whether writing experience has an impact on learning letter name/sound knowledge. Additionally, participants have typically performed very accurately on the limited assessments that have been used, raising the concern of ceiling effects that preclude identifying differences in learning outcomes across learning experiences. Thus, it has been difficult to assess whether null results are due to a true absence of differences. Finally, without sufficient training and assessment of letter learning, it is difficult to examine the content of the letter representations that are learned.

Low Educational Relevance

Relatedly, there has been little ecological validity to tasks used to evaluate learning outcomes. For the purposes of informing best practices in the classroom, it would be preferable to demonstrate learning that is relevant to the classroom—in the case of learning letters, the goals of the teacher include learning the names/sounds of the letters and their mapping to the physical shapes. To date, assessing these aspects of learning has not been possible because they require more extensive training and/or assessments than have been previously used (but see Zemlock, Vinci-Booher, and James, 2018). In other words, participants have not been required to discriminate the letters they are learning from one another, which is a central goal of teaching in the classroom. Furthermore, because letters are typically taught simultaneously both for purposes of word-reading and spelling/writing, an additional goal would be for students to be able to read and spell short words; to date such tasks have not been administered in the experimental literature.

Matching Learning Experiences to Eliminate Confounds

In the experiments discussed in section II, the learning experiences were not always well matched to ensure as much as possible that differences in outcomes were due to intrinsic properties of the specific learning experience, and not incidental task-related factors. For example, the different learning experiences have not all been well matched for the “time on task" during the learning trials: participants in a visual condition (asked to simply view the letters and memorize their shapes) may spend less time learning the letters than participants in a motor condition, and so differences in performance could be the result of the amount of exposure to the stimuli, and not specific properties of the learning experience *per se*. A subtler but potentially important difference between writing and typing or visual study is that writing provides exposure to variable exemplars (see section IV, "Variable Visual Input"), *and also* perception of motion. In other words, not only do individuals in writing conditions produce letters by hand, they also perceive the movements of the hand and pen, and the handwritten exemplars. One study (Kersey & James, 2013) controlled for the variable of motion perception, by including a condition in which children viewed an adult experimenter writing the letters, but did not write themselves. The result of this study was that sensory/motor cortex activity during letter viewing was found only for children who had writing experience, not those who observed writing by others. However, there were no behavioral differences found between these two groups, once again suggesting that the sensory/motor activity may be not be causally related to behavioral benefits. As mentioned in the Introduction, it is possible to dissociate knowledge of how to perform an action and knowledge of what that action looks like (Casile & Giese, 2006), but this requires either experimental manipulation of the learning conditions, or information about the content of the learned representations (i.e., determining whether the representations are motoric or visual).

Retention

Only two studies (Longcamp et al., 2006, 2005) tested learning retention. These two studies found that significant behavioral differences between learning letters through writing versus through typing emerged only one to three weeks after the completion of training. This suggests the possibility that an important difference between the learning experiences is the durability of the learned representations, but this has not been thoroughly investigated.

The Content of Letter Representations

No study that has manipulated learning experiences has examined how letters are represented, or how those representations are affected by the learning experience. Letter representations can be found in multiple modalities, and SLI are amodal representations. These various types of letter representations have been substantiated both through behavioral techniques and neuroimaging methods (as outlined in section III of this chapter). However, the relationship between these representations and the effects of learning experience, motor or otherwise, is unknown. It is clearly problematic that no experiment has yet provided evidence of whether indeed any differences exist in the representational space of letters in accordance with how the letters were learned.

VI. Informing an Account of Learning Letter Representations

Taken together, the accounts of why writing might affect letter learning for reasons other than motor representations (section IV. "Writing Experience Entails More than Motor Experience", pages 41-49) and the various limitations of previous research on letter learning (section V. "Addressing Outstanding Issues") reveal why it is premature to draw conclusions about how writing experience "matters" for letter learning. Indeed, the behavioral effects of writing experience on letter processing tasks are unclear, and it is problematic that the neural effects, although consistently reported, have never been associated with any behavioral effects. The conclusions that are most sound are: (1) sensory/motor cortex activates in response to passive viewing of single letters; (2) this activation is present only for observers who have experience writing those letters; (3) experimental conditions where participants learn letters through writing tasks tend to lead to more accurate letter recognition tasks. These facts do not support conclusions regarding the content of the letter concepts nor whether those concepts are affected by the nature of the learning experience. They also do not show that writing experience is necessary for any letter processing task. Nonetheless, researchers and the interested public alike have sought to use this evidence to support two broad points: sensory/motor representations are causally implicated in letter processing tasks generally, and writing experience may be critical for learning a written language. This section therefore concludes the chapter by elaborating on the three primary questions addressed by this dissertation, explaining how answering them has broad theoretical and practical implications regarding the role of writing experience on letter learning.

Question 1: Are the effects of writing experience due to motor learning *per se*?

It is critical to know whether writing experience affects letter learning due to the learning that takes place only through producing letters by hand, or due to some other factor that is associated with the writing conditions. Should it be found that the relevant components of writing experience are peripheral to the actual writing process, then it is implausible that the underlying representations are motoric in nature. Moreover, the practical implications would be that at best, writing is a convenient method of instruction, but some other training might focus on the relevant components—in other words, it would suggest that decreased instructional time for handwriting is not necessarily detrimental for learning letters.

The existing research on the effects learning experiences on letter acquisition has been challenged to address the possibility that differences across conditions might be explained by factors as basic as time on task, for example with more time being spent writing letters than studying them by vision or by typing. In order to address this concern, the learning experiences used in the longitudinal training study here were designed so as to equate exposure to the letter stimuli in a number of ways: (1) the maximum amount of time spent on each letter was equated; (2) all participants were presented with visual information of the letters dynamic (i.e., animations), so that the writing experience is distinguished primarily by its motor components, and not additionally confounded by the dynamic visual information that is typically available only during handwriting. This is a particularly important point, and only one study (Kersey & James, 2013; Li & James, 2016) thus far has produced results that potentially adjudicate between whether it is motor activity *per se*, or the dynamic visual information that is necessarily associated with handwriting, that informs letter perception; (3) a wider range of behavioral measures was used, in part to address a pure effort account, which predicts that the most "effortful" condition should perform better on a range of tasks; (4) participants in all learning experience conditions were trained to common criteria on a letter recognition task; and (5) measures of the amount of time participants spent completing their task during learning were compared to behavioral performance on other measures, to verify that relative amounts of effort are not predictive.

To somewhat anticipate results, an effort account is thus seen to be insufficient to explain the motor-perceptual link.

Question 2: Does writing experience recruit only sensory/motor representations?

The answer to this question addresses the possibility that the effects of writing experience are not incidental to the motor learning aspects, but at the same time are not *limited* to motor representations. Put otherwise, the effects of writing experience could extend beyond knowledge of how to write the letters, and accordingly the source of differences across learning experiences could be other types of representations, including amodal ones. This is particularly important for supporting or refuting grounded cognition theories that assume activity in "sensory-motor" cortex actually reflects sensory/motor representations. This activity could represent information other than motoric, especially so because the term "visual-motor processing system" (James, 2017) often refers to areas beyond primary somatosensory and motor cortices. For example, this activity could reflect representation of the visual dynamic information learned from observing hand movements (although see Kersey & James, 2013, for evidence that this is not a full account of the effects of writing experience). Alternatively, this activity could also reflect "higher-level" orthographic representations, such as SLI, and as such could be amodal in nature. Such evidence would not specifically support a grounded cognition account, and would in general be supportive of abstractionist theory. This question has not been entertained as such in previous research, and no data has been collected to provide insight into what types of letter representations arise under different learning conditions. Thus, this dissertation addresses this question directly, by obtaining both behavioral and neural measures that reveal the content of letter representations (behaviorally via a same/different judgment of pairs of letters, and neurally by RSA analysis of fMRI data).

Question 3: Which types of representations underlie the behavioral benefits of writing experience?

The popular account that writing experience leads to better letter learning is ultimately based on finding that children show adult-like brain activity in response to letters only if they have learned how to write those letters, together with evidence suggesting better performance on some basic letter processing tasks. However, there is a misconception in this popular account that the two have been associated with one another—that is, nothing has in fact indicated that the brain activity specifically in sensory/motor cortex underlies any of the purported behavioral advantages for writing experience. And while motoric letter representations have been found to influence behavior on perceptual tasks like the same/different judgment, they have not been related to the ability to use letters in actual language tasks (reading or spelling). In order to make a strong claim for a causal role of writing experience in letter learning, it is necessary to show that neural-behavioral associations are mediated through sensory/motor representations. The dissertation addresses this final question first of all by administering assessments of language tasks including reading and spelling (which has not previously been done), and secondly, by further investigating the relationship between performance on those tasks and the location and nature of the letter representations observed in the brain via the RSA technique.

Chapter 2 – Methods & Analyses

This chapter describes how the influence of motor experience on the learning of letters is assessed in this dissertation. The chapter is divided into sections as follows. The first two sections present the behavioral (I. "Behavioral Methods") and the neural (II. "Neural Methods") approaches used to address the primary questions of interest. Details are given about the experiments conducted for each of these two approaches, as well as information about the overall structure of the longitudinal study (i.e., what tasks were administered and when) and about particularities of the Arabic alphabet that have a bearing on understanding the results. The next sections explain the approaches taken for analyzing the data from the various tasks (sections III. "Behavioral Analyses" and IV. "Neuroimaging Analyses"). A final section (V. "Primary Aims") summarizes the methods and analyses by revisiting the three primary questions of the dissertation. It clarifies exactly how the experimental design and results of the analyses allow for answering the three questions (discussed in previous chapters) addressed in the dissertation.

I. Behavioral Methods

An overview of the various training tasks and behavioral assessments is depicted in the top panel of Figure 2-1. In total, six behavioral assessments were administered at one or more time points, in addition to training tasks that were performed over the course of multiple sessions as participants learned the shapes, names, and sounds of 20 Arabic letters. There were three learning Conditions: Typing (T), Visual (V), and Writing (W), designed to manipulate the experience that participants had while studying the Arabic letters. Only the last of those conditions, the Writing Condition, is a true motor condition, whereas the Typing and Visual Conditions represent different non-motor experiences. Assessments were administered at multiple time points in order to evaluate the learning outcomes, as well as the trajectory of learning over the course of the study, in order to determine whether or not these differed as a result of the learning conditions. The time points included pre-tests (i.e., assessments prior to any learning of the Arabic letters), training (assessments during training sessions), post-training (assessments after reaching stopping criteria on training), and follow-up (assessments one month after post-training). The details of the assessments are as follows.

	Pre-tests	Training	Post-training	Follow-up
Behavioral	• Same/different judgment	• Training tasks (typing, vision, writing) • Letter recognition	• Letter recognition • Letter naming • Dictation (letters & words) • Word reading • Same/different judgment	• Letter recognition (standard and novel font) • Letter naming • Dictation (letters only)
fMRI	• Letter Learning Network (LLN), 2 runs • Symbol Detection Task (SDT), 8 runs	--	• LLN, 2 runs • SDT, 8 runs	--

Figure 2-1. Study schedule from pre-training to follow-up, with behavioral tasks (top row) and neuroimaging (fMRI, bottom row). LLN = Letter Learning Network. SDT = Symbol Detection Task.

Participants

42 participants were recruited from the greater Johns Hopkins community, with 14 assigned to each of three learning experiences. The participants were selected to have no history of learning disabilities or any previous experience with Arabic, as determined by a screening questionnaire. The sample size was intended to improve upon previous similar studies (e.g., Longcamp et al., 2006). The participant demographics are reported in Chapter 3 in Table 3-1. Thirty-six participants completed the study through the post-training time point (see Figure 2-1), and thirty-three participants completed through the follow-up time point. There was a payment of $10 per session, including pre-tests and post-training sessions, and a $20 payment for completing the follow-up session.

Stimuli

The Arabic alphabet consists of 28 unique letter identities, each of which has between 1 and 4 distinct shapes (allographs), for a total of 52 different letter-shapes. A subset of 20 letter identities was selected from the full set of Arabic letter forms based on the following criteria: (1) to avoid selecting pairs of letters whose names are difficult for English speakers to distinguish (for example, the IPA-coded /t/, like English "t", and the emphatic version /t'/ which is pharyngealized), (2) to avoid, as much as possible, shapes which are essentially indistinguishable from shapes of certain Roman letters (Wiley et al., 2016), so that all letters require learning to discern novel shapes, and (3) to include letters that have highly visually *dis*similar allographs, so as to be able to better tease apart visual representations from symbolic letter identity representations. The final list contained 17 consonants and 3 vowels. 13 of the consonants and 1 of the vowels have 2 allographs, while the remaining 6 letters have only one, resulting in a total of 34 letter-shapes. Four different fonts (Figure 2-2: Adobe Arabic, Nadeem, Myriad, and Farisi) were used for the training stimuli. The font Adobe Arabic was used in all other tasks, including neuroimaging, unless otherwise noted.

During training, both single letters and short 2-3 letter words were presented to participants. The single letters were used to teach the letters' name and sound (see "Training Session Procedure"). Briefly, each letter was presented in a dynamic display (animated using the software Adobe AfterEffects), showing the letter as though it was being written on the screen, and was accompanied simultaneously with audio of the letter's name and sound (e.g., "alef", "ah"). While most Arabic letter-shapes map onto one unique sound, a few are ambiguous either because they represent semivowels (e.g. the letter name "waaw" represents both the consonant /w/ and the vowel /u/), or because they represent vowels which change quality in the presence of emphatic consonant (e.g. /ae/ becomes /ɑ/). For the purposes of the training, each letter -shape was presented as having only one unique sound (specifically, alef as /ae/, waaw as /u/, and ya as /i/) so that there was always a one-to-one mapping of shape onto sound (although there were one-to-two mappings of sounds onto shapes, for the 14 letters that have two allographs; see Figure 2-2).

The short words were created by pairing each of the 17 consonants (C) with each of the 3 vowels (V) to create three words for each consonant-vowel pair: CVC, CV, and VC. In the CVC words the same consonant occurred twice. Which vowel appeared in which syllable was random. For example, the consonant "kaf" (/k/) was used to make the pseudowords /kik/, /ku/, and /ak/ by pairing respectively with the three vowels /i/, /u/, and /a/, whereas the consonant "fa" (/f/) was paired with the vowels so as to may /faf/, /fi/, and /uf/. This process created 51 words (17 consonants x 3 words for each). These words were presented during training for two different purposes. First, because Arabic is a cursive writing system, some of its properties become manifest only in the context of words: the direction of writing (and reading), the relationship between allographs and their position within the word, and the order of certain strokes. Indeed, many of these properties arise from how Arabic words can be divided into sub-words, which are the subsets of letters within words defined by the pattern of ligating and non-ligating letters (i.e., a gap in a word following a non-ligating letter creates a new sub-word). Figure 2-3 clarifies these properties as follows: (A) Arabic is written (and read) from right-to-left, which is not apparent in the context of single letters. (B) Allographs such as the two shapes of "kaf" are predictably related to their position in the sub-word. (C) The typical ordering of strokes is influenced by the need to write entire sub-words in cursive, i.e., certain strokes are added after the "frame" of the sub-word. The second purpose of the word-blocks was to provide participants with some experience with words to facilitate post-training assessment of their ability to read and write whole words. As previously discussed (see Chapter 1), no previous study has examined whether the effects of motor experience on letter learning extend beyond processing of single letters. No definitions were given for the words (which included a mix of real Arabic words and pronounceable[7] pseudowords).

[7] Pronounceable according to English phonotactics. The teaching and learning of phonology is largely outside the scope of this experiment, apart from learning some letters whose phonology does not exist in English (e.g. "qaf", /q/, the voiceless uvular plosive). Therefore, all words used for training or assessment of reading ability conformed to the phonotactics of English and not Arabic.

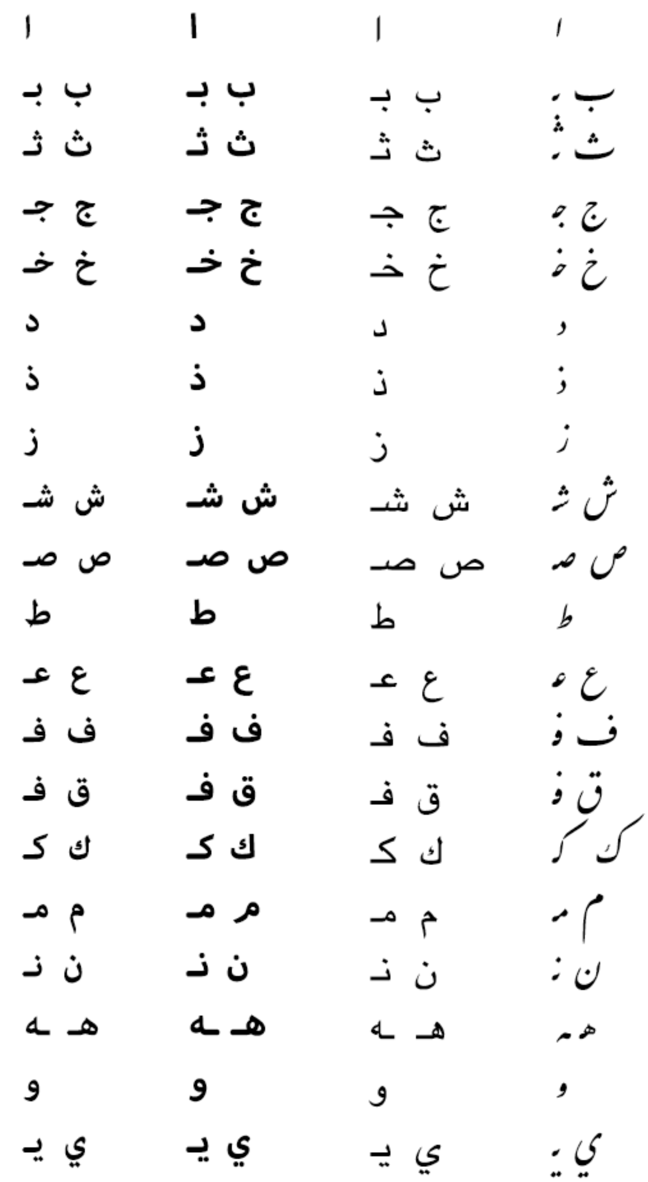

Figure 2-2. All stimuli for the learning experiences. The 20 letter identities are listed vertically, with allographs side by side. The four fonts are, from left to right: Adobe Arabic (default font), Nadeem, Myriad, and Farisi.

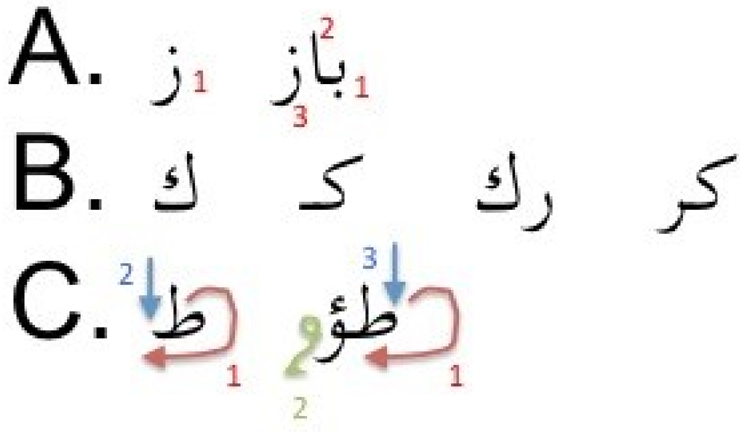

Figure 2-3. Properties of Arabic conveyed only in the context of whole words. The letters on the far left are all written in their "isolated" (unconnected) forms. The numbers indicate order of the strokes. (A) The letter "zay", which looks like a lowercase Roman "j", is written and read *last* in the word "baz" (right). (B) The two allographs of the letter "kaf" are selected based on whether they are initial in a sub-word (far right) or isolated in a sub-word (third from left). (C) The letter "tau" (left) is written by the loop first, followed by a descending vertical line. This order (both prescribed and preferred by Arabic native speakers) facilitates the connection of "tau" within sub-words; for example, the descending vertical line would be written last in this segment in order to continue from the initial stroke smoothly into the second letter.

Training Session Procedure

Each training session consisted of two stages, a training stage and an assessment stage. In the training stage, there were four blocks of study trials: three letter-blocks and one word-block. The first three were letter-blocks, consisting of 80 trials over 8 minutes, and within these blocks each of 20 different letter identities were presented four times, in random order: either two allographs in two different fonts, or one allograph in four different fonts. The rationale for including multiple fonts was twofold: (1) In order to expose participants *in all conditions* to variability in the input, which has been found to be an important factor in learning to recognize letters (see Chapter 1; also, Li & James, 2016); (2) because some Arabic letters do not have a second allograph (including 2 out of the 3 vowels), including multiple fonts allows for each letter *identity* to be presented as multiple shapes, supporting the possibility of learning SLIs.

The fourth block of each training session was a word-block consisting of 51 trials and lasting 8.5 minutes. Each of the 51 short words (see "Stimuli" above) was presented once, resulting in each consonant being presented four times. Letter identities corresponding to vowels were necessarily used more than consonants, for a total of 17 times each per word-block. In total, one training session thus consisted of 16 presentations of each consonant and 29 of each vowel, across the four blocks of study. The structure of the individual trials within the letter- and word-blocks is described in the next section.

In the second stage of the training sessions, participants were assessed on their letter learning with two tasks: a letter recognition test, and a letter naming task. The letter recognition task was used to determine when stopping criteria for training had been reached (see "Training timetable and post-training time point criteria), and to provide a longitudinal measure of the learning trajectory. The details of both of these tasks are provided in the section "Behavioral Assessments".

Structure of the Training Trials

On each training trial, participants viewed dynamic displays of the letters/words as if being written by hand on the screen (see Figure 2-4). The trials differed slightly depending on whether they were in letter-blocks or word-blocks. (**1) In letter-blocks,** each dynamic display was presented simultaneously with audio of the letter's name and sound (e.g., "alef", "ah"). Participants were told to learn the letter's shape, name, and sound, and that they would be tested on this knowledge. The trials were 4 seconds long in total (Longcamp, Boucard, et al., 2006), with the dynamic image unfolding at a rate of 1 second/letter and the audio over the first 2 seconds. The static image remained onscreen for 3 seconds. See Figure 3-2 for a schematic of the trial structure. (**2) In word-blocks**, each dynamic display presented a two-to-three-letter word simultaneously with audio. The trials unfolded in the same manner as in letter-blocks, except with the static image remaining on screen for an additional 5 seconds, bringing the total trial length to 9 seconds. No definitions for the words were given (which included a mix of real Arabic words and pronounceable pseudowords). During each training trial, participants performed a task according to their assigned learning Condition: Typing, Visual, or Writing.

For all conditions and in both letter- and word-blocks, a tone played at the end of each trial indicating a 1 second intertrial interval with a blank screen. The task instructions for each learning Condition were as follows:

(1) Typing Condition—The task was to find the letter(s) presented dynamically on each trial on a keyboard, which was modified with Arabic letter stickers on the keys, and to press the corresponding keys (in the correct sequence, for words). The participants were instructed to complete this task as quickly and accurately as possible, within the time limits of the trials: 4 seconds in letter-blocks and 9-seconds in word-blocks, which included 3 seconds and 6-7 seconds respectively during which the letter(s) was/were displayed statically on the screen. The keyboard was modified by adhering opaque labels to a regular

US English keyboard. For those letters with multiple allographs, different keys were used for each shape (e.g. "A" and "a" would both appear on the keyboard, but on different keys). This was done to avoid giving participants in the Typing Condition specific information about SLIs for allographs (i.e., if allographs appeared on the same key, it would be an extra clue to their shared identity, unavailable to participants in the other learning conditions). The font used on these labels was Adobe Arabic, one of the four fonts used in the training and also the font used for all other behavioral tasks presented to participants via computer or print (e.g., during post-tests). The letters were arranged on this keyboard in the same layout for all participants and all sessions; this layout was the result of a randomization of the 34 letter-shapes into three rows (seven, seven, and six) in the center of the keyboard, with the only constraint that no highly visually confusable letters were adjacent to each other. Visual confusability for this purpose was determined on the basis of earlier work on the naïve perception of Arabic letters (Wiley, Wilson, & Rapp, 2016). Both reaction time and accuracy were recorded on each trial.

(2) Visual Condition—In this condition, the participants performed a visual detection task. The dynamic display was identical to the Typing and Writing Conditions, however the static image persisted for only 1 second before disappearing. It was followed by a 500ms blank screen, a 66ms fixation cross, and then a 1000ms probe. The probe was either a non-alphabetic symbol (e.g., ?, %, #) or the target Arabic stimulus in a smaller font. After the probe, the target Arabic letter returned for the remainder of the trial (1433ms in letter-blocks or 4.433-5.533ms in word blocks; see Figure 2-4). In this way, the total trial length remained the same as in the other conditions. The task was to indicate by pressing one of two keys whether the probe matched the identity of the target letter or not. The purpose of this task was to ensure that attention was paid to the stimuli throughout the trial, in an effort to equate time spent on task in this condition with the two other conditions.

(3) Writing Condition—The procedure was identical to the Typing Condition, except in place of the typing task, participants had to copy the stimuli. Participants wrote the letters/words with pen on ruled paper placed atop an electronic tablet (Wacom Intuos) connected to the E-Prime 2.0 software (Psychology Software Tools, Pittsburg, PA). This recorded the onset time of writing, allowing analysis of changes in reaction time over the course of training. The stroke patterns to be used were not explicitly prescribed, however they could be inferred based on the dynamic image presented on the screen.

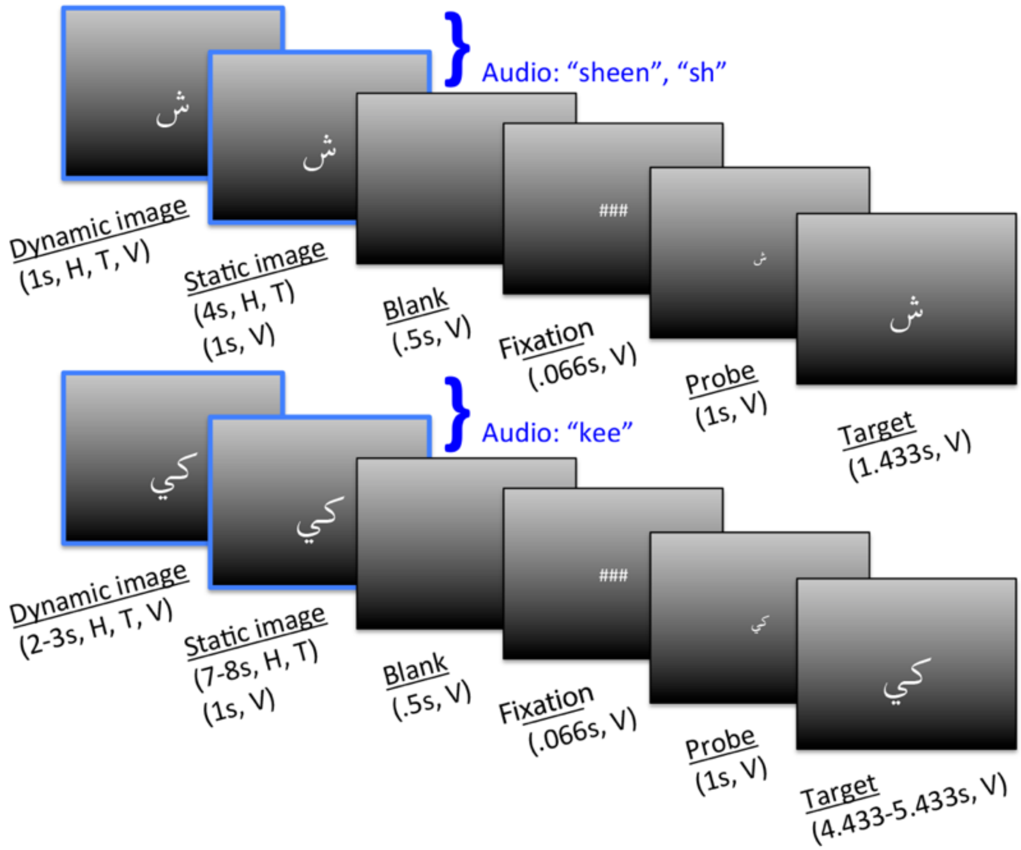

Figure 2-4. Trial structure of training phase. Top: Letter-blocks, Bottom: Word-blocks. H=Handwriting, T=Typing, V=Visual.

Training Instructions and Feedback

Immediately prior to beginning the first training blocks, the participants in all learning conditions were told that Arabic is written from right to left and in cursive, and that most letters they see would have two shapes. It was explained to them that in Arabic, the letter-shapes change depending on neighboring letters in words. On this point, they were given the example of cursive lowercase “l” differing somewhat in its shape depending on whether it is written followed by an “e” or an “m”.

The experimenter then showed the participants each letter used in the experiment printed on a flash card (Adobe Arabic, font size 24), in random order. The experimenter reminded them that they would be asked to learn the shapes, names, and sounds of the letters during training, but that during this "preview" they would have the opportunity to hear each letter's name and sounds clearly. The flash cards were reviewed twice: once, with the experimenter asking the participant to repeat the letter name after them, and a second time, asking them to repeat the letter sound. In this way, it was assured that participants understood the distinction between the letter name and sound (and they were also given the example of English [A]: name /ei/, sound /æ/). Moreover, participants were given the opportunity to have the letter name or sound repeated, if they did not understand it, and were asked to repeat it themselves more than once, if they had misheard[8]. The flash cards were not reviewed again at any later time point, although the participants were allowed to ask for clarifications about what they heard in their training videos at any point.

Pilot testing indicated that participants in the Typing or Writing Conditions might stop paying attention to the dynamic display, relying on the audio to produce their response without watching the screen. To diminish the likelihood of this approach to the training tasks, in all conditions 25% of the trials were silenced at random, thereby preventing a participant "strategy" of completing the task by listening to the audio only, at the expense of paying attention to the dynamic image. As for feedback, for the Typing and Visual Conditions, once a response was made, a tone indicated whether the response was correct or incorrect;

[8] For example, the letter ذ /ðæ:l/ and sound /ð/ was often misheard as /væ:l/ and /v/-- the experimenter would clarify this for the participants, saying "No, it's not V like Valerie, it's TH like This".

a distinct third tone marked the end of each trial if no response was recorded at all. For the Writing Condition, no formal feedback was given, but participants were able to view their own handwritten exemplars and compare them to the stimuli on the screen.

Training Timetable and Post-test Time Point Criteria

Training sessions took place twice a week, with a minimum of one day in between sessions (i.e., no sessions on consecutive days). At the end of each training session two short behavioral tasks were administered to provide longitudinal measures of learning: a letter recognition task and a letter naming task. These were administered identically across all three learning conditions, and the first of these was used to determine when stopping criteria were reached, as follows:

Training to Criteria: Performance on the letter recognition task administered at the end of each training session was used to determine readiness for the post-training tasks, as well as the post-training neuroimaging session (see section II. "Neural Methods"). Specifically, all participants had to fulfill two criteria: greater than 90% accuracy, and a 25% reduction in RT relative to performance on the first administration of the task (i.e., after one training session). Moreover, this performance level had to be maintained across two consecutive sessions, or else training was continued, for a maximum of six training sessions. The purpose of these criteria was two-fold: (1) to assure some comparability in performance level across the three learning conditions, and (2) to assure some stability of the learned letter representations, which was particularly important for the participants completing the neuroimaging sessions (as those scanning sessions necessarily took place at a later time point; see section II. "Neural Methods").

Assessment Timeline: The pre-test time point consisted of all tasks completed prior to beginning training: the Same/Different Judgement task of both Arabic and Roman letters, and the first neuroimaging session (see Figure 2-1). Training began at any point after the pre-tests, ranging from 2-52 days later. Post-training tasks (Letter Recognition task, Letter Naming task, Writing Letters to Dictation task, Spelling Words to Dictation task, and Reading Words task) were completed after reaching criteria, ranging from 2-5 days later. For participants undergoing neuroimaging, the second neuroimaging session was scheduled as soon as possible after the post-tests, ranging from the same day to no more than one week later[9]. Follow-up tests (Letter Recognition task, both regular and Novel Font, Letter Naming task, and Writing Letters to Dictation task) were completed approximately one month after the post-tests (ranging from 16-40 days). The details of each of these tasks are presented below.

Behavioral Assessments

The following tasks were administered to all participants, identically across all three learning conditions. (See Figure 2-1).

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[9] Participants who were unable to complete the second neuroimaging session within a week after post-tests, due to scheduling conflicts, were brought back for an additional training session. This "refresher" training session consisted of the learning condition tasks (both the 3 letter-blocks and 1 word-block) but none of the other assessments. In total, just 4 of the 24 neuroimaging participants completed refresher training sessions.

(1) Same/Different Judgement task: All participants performed same/different judgments on pairs of letters from both the Arabic and Roman alphabets, at both the pre-training and post-test time points. The procedure of the task was as follows: a 250ms fixation cross was followed by simultaneous side-by-side presentation of a pair of letters, for a maximum of 2000ms or until a response of either "same" or "different" was made. The Arabic and Roman letters were presented separately (i.e., as two distinct experiments, but otherwise all pairwise combinations of the letters were used, for a total of 66 different pairs per alphabet. The stimuli were two allographs each of 6 Arabic and 6 Roman letters (for a total of 12 letter-shapes per alphabet), corresponding to those also used in the neuroimaging task (see "Neuroimaging Methods"). The Same/Different Judgement task is useful for two reasons. First, it is possible for naïve observers to complete this task, and the accuracy and reaction times can be used to provide a measure of perceptual representations. Wiley, Wilson, and Rapp (2016) used this task with two participant groups, one naïve and one expert and their findings provide expectations for naïve observers' perceptions of the Arabic letters in this study, and how these might change as a consequence of the training, as discussed in Chapter 2 (section "Multiple Representations of Letters").

(2) Letter naming task: A letter naming task, also known as a discrete rapid automatized naming task (RAN, de Jong, 2011) was administered at the end of each training session, as well as at post-test and follow-up time points. All training letters were presented individually using E-Prime Professional software, recording voice onset time, with the experimenter manually recording accuracy. A response was scored as correct as long as it unambiguously referred to the correct letter, regardless of the accuracy of the participant's actual articulation. Each letter-shape was presented twice, for a total of 68 trials. Letter naming ability is known to be a strong predictor of reading acquisition in children cross-linguistically (McBride–Chang & Kail, 2002), and have been found to explain variance in reading abilities across children independent of phonological skills (Mazzocco & Grimm, 2013). An additional appeal of letter naming for this study is that it requires mapping between letter names and shapes, an ability which would not obviously be supported by any one of the learning experiences over another.

(3) Letter Recognition task: A letter name was presented aurally (using the same audio files as the training videos) and participants had to select the corresponding letter-shape from an array of 4 letters, by clicking on it with the mouse cursor. This task was presented at the end of each training session, just prior to the letter naming task, as well as at post-test and follow-up time points. This task and the letter naming task together are the closest match to actual classroom assessments, that typically require students to associate letter shapes and names. Each of the 34 letter-shapes were presented 4 times using E-Prime Professional software. This task was self-paced, as between each trial participants had to return the mouse cursor to the center of the screen and click on a small fixation cross, after which the audio of the next letter immediately played and the four choices were presented equidistant from the cursor in the center of the screen. Both accuracy and reaction time were recorded. The distractor choices were chosen based on visual and letter-name similarity—specifically, all of the distractors were those that were previously established as being most visually confusable (Wiley, Wilson, & Rapp, 2016) but excluded distractors with highly similar letter names. This maximized the difficulty of the visual discrimination component of the task, while minimizing the potential complication of auditory comprehension. The correct target appeared once in each of the four possible locations, and trial order was randomized on each session. Performance on this task was used to determine readiness for the post-test sessions (see this chapter, section "*Training timetable and post-test time point criteria"*).

(4) Novel Font Letter Recognition task: at the follow-up time point the participants were also given this task that was identical to the letter recognition task that was administered repeatedly, with the difference that the stimuli were presented in one of two fonts which they had never seen before (see Figure 2-5).

(5) Writing Letters to Dictation task: Each of the 20 learned letter names was presented aurally and participants were asked to write the shapes of the letter from memory; participants were reminded that most of the letters had two shapes, and were prompted to produce both if they could remember both. This task was administered at post-test and again at follow-up. It is the only task (outside of performance on the training trials themselves) to address direct effects of learning experiences (see Chapter 1, "Direct and indirect effects of learning experience"), as it requires some of the same processes which were trained in the Writing Condition. Responses had to meet three criteria in order to be scored as fully correct: (1) they had to include the features necessary to make them distinct from other letters in the set (e.g., for Roman letters: missing the dot on a lowercase "j" would not be scored as incorrect, whereas not crossing the lowercase "t" would be); (2) they could not include any additional features, which might be taken to as intrusions from other letters (e.g., adding a dot over a lowercase "t" would be scored as incorrect), and (3) they could not be mirror-reversed. As such, each response was categorized as either (a) correct, (b) distorted (e.g., lacking features or having additional features), (c) mirror-reversed, or (d) non-response (i.e., nothing was written). Participants wrote the letters on an electronic tablet (Wacom Intuos Pen tablet).

(5) Spelling Words to Dictation task: Immediately following the Writing Letters to Dictation task at the post-training time point, the participants were presented with audio of whole words, and asked to attempt to write them (on the electronic tablet). The stimuli included 20 words, ranging in length from 3 to 6 letters, including both familiar words they had seen in training (seven 3-letter words) and novel words. In order to focus evaluation on knowledge of the correct letters in this task, as opposed to the motor processes necessary for producing a well-formed written responses, these responses were scored with no penalty for mirror-reversed letters, for incorrect allographs (i.e., akin to using an uppercase letter in the middle of a word), or for distorted letter-shapes, as long as the intended letter was unambiguous (for example, adding a dot above the "t" while spelling "tea" would be scored as correct). Furthermore, responses were scored as the percent of letters correct, thus awarding partial credit to words that were not spelled completely correctly.

(6) Reading Words task: Words ranging in length from 2-6 letters were presented to the participants for oral reading, only at the post-test time point. The stimuli included 20 words in total, 7 of which were familiar from training during word-blocks. Participants were allowed to spend as much time as they liked to try to read the word. They were prompted to try to sound the word out if they could, or else to name the letters individually if they were unsure of the sounds or unable to blend them together. Thus, the responses were scored in two ways: first, as the percent of letters correct (e.g., reading "cat" as "at" would receive a score of 2/3), and second, as the percent of letters identified (e.g., reading “cat” as “see, ay, tee” would receive a score of 3/3).

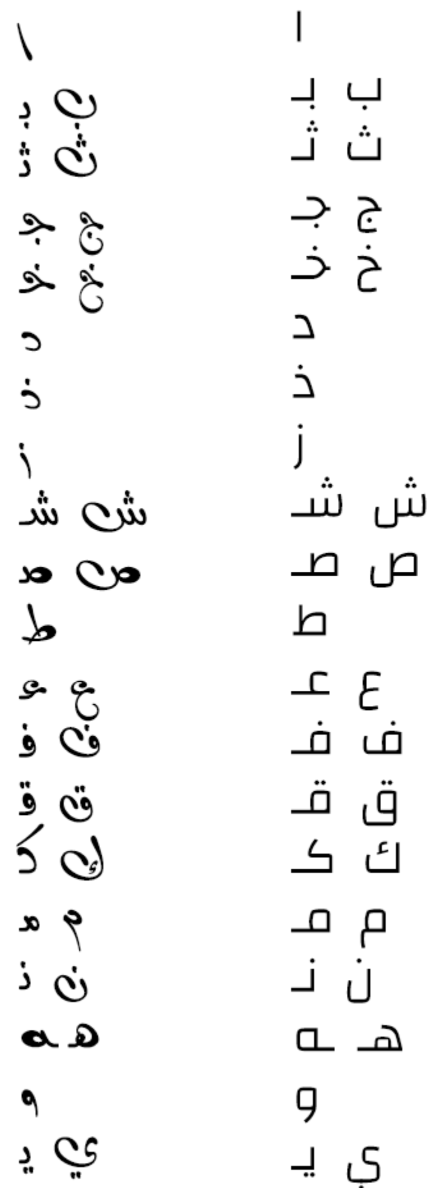

Figure 2-5. Fonts presented in the novel font letter recognition task (at follow-up time point): Basim (on the left) and Changa (on the right). Compare to familiar fonts, presented during training trials, in Figure 3-3.

II. Neuroimaging Methods

An overview of the neuroimaging assessments is depicted in the bottom panel of Figure 2-1. Two fMRI tasks were administered in identical scanning sessions at both pre-training and post-training time points (see "Training Timetable and Post-test Time Point Criteria"). Briefly, these two tasks were: (1) Letter Learning Network (LLN) task, which was used to localize brain regions whose activity changed from pre- to post-training selectively in response to Arabic letters, and (2) Symbol Detection Task (SDT), which was used to determine the pattern of activity in response to single Arabic letters, within regions of interest. Previous examinations of the effects of motor versus non-motor learning experiences have drawn conclusions based exclusively on the strength and location of neural activity (BOLD signal). The one exception was the study of Vinci-Booher et al. (2016), who conducted a functional connectivity analysis of previously-reported data (James & Engelhardt, 2012). In that study it was reported that functional connections increased more for children who had writing training than typing training, between visual regions and both parietal and frontal regions. However, neither this nor any other study has investigated the representational *content* of the activity in these regions in response to letters. The neuroimaging methods detailed below were therefore used to reveal the nature of the letter representations (sensory/motor and/or amodal) and how they were affected by the learning condition, using Representational Similarity Analysis (RSA; see section IV. "Neuroimaging Analyses").

Participants

Of the total 42 participants, a subset of 27 , 9 per learning condition, were randomly selected (given their willingness to participate) to undergo two fMRI sessions, one before and one after training. Specifically, the first neuroimaging session took place before any of task or training was completed, with the exception of the Roman letter Same/Different Judgement, while the second neuroimaging session took place within a week after the post-training assessments (see Figure 2-1). Participants were paid $50 per scanning session. The participants ranged in age from 18 to 31 years old (see Chapter 4, Table 4-1 for demographic information)., and all had normal or corrected-to-normal vision.

Neuroimaging Tasks

During the scanning sessions, participants were administered two different tasks, repeated identically at both time points:

(1) Letter Learning Network (LLN) Localizer task—Participants viewed 4 blocks of each of the following block types: Arabic letters, Roman letters, English words, and checkerboard patterns. Each 15-second block consisted of 10 different stimuli. The stimuli were all of the same height (63 pixels) and ranged in width from 20 to 233 pixels. The instructions were to press buttons (one held in each hand) whenever either a non-alphabetic symbol (%, *, ~, &, at the end of blocks of letters) or a boy's name (e.g., Michael, at the end of word and checkerboard blocks) appeared. Participants completed 2 runs of this task.

(2) Symbol Detection Task (SDT)—Participants viewed single letters in an event-related design, and responded by pressing buttons in both hands whenever a non-alphabetic stimulus appeared. Participants completed 8 runs of this task, alternating between Arabic and Roman letters (4 runs each), with the order randomly assigned to participants. The same order was maintained across the two neuroimaging sessions. Each trial consisted of: fixation for 200ms, stimulus for 300ms, and a jittered post-stimulus blank (1500ms, 3500ms, or 5500ms, on average 3500ms). Each run consisted of 64 trials in random order (48 letter-shapes, 16 symbols), and lasted 4 minutes, 30 seconds in total (including an additional 14 seconds of fixation at the start and end of the run). Each letter-shape was presented 4 times per run, for a total of 16 presentations across the session.

Stimuli: As with the procedure of Rothlein & Rapp (2014), 12 letters (two allographs each, 24 letter-shapes) were included along with 4 non-alphabetic symbols (%, *, ~, &). 12 letter-shapes were from the English alphabet (a, A, b, B, e, E, g, G, q, Q, r, R) and 12 from the set of Arabic letter-shapes (ب، بـ، ج، جـ، ش، شـ، ق، قـ، ك، كـ، ي، يـ). The Roman letter-shapes were presented in Arial font size 80, the Arabic letter-shapes in Adobe Arabic font size 120 (equating the maximal heights of the two alphabets), as white text on black background. The letters were chosen on the basis that they have visually dissimilar allographs, and because pilot testing revealed that these Arabic letters tended to be the most readily learned (both their shapes and names).

Scanning Protocol

In addition to neuroanatomical scans, as described just above each session consisted of two tasks presented for a total of 10 task-based runs. MRI data were acquired using a 3.0-T Philips Intera Scanner. Whole-brain T2-weighted gradient-echo EPIs were acquired with an eight-channel SENSE (Invivio) parallel imaging head coil. Structural images were acquired using a standard MP-Rage T1-weighted sequence yielding images with 1 mm isotropic voxels (repetition time = 8.036 ms, echo time = 3.8 ms, flip angle = 8°). All functional runs were set to a TR = 2s. Total scanning time for all task-based functional runs was 46 minutes.

III. Behavioral Analyses

Linear Mixed Effects Models: General Analysis Approach

The general analytical approach to the data from the various behavioral tasks (described in I. "Behavioral Methods") is described in this paragraph. Details about specific variations are described in subsequent subsections. (1) For the data from each of the tasks, the effects of learning Condition (Typing, Visual, and Writing) were analyzed using generalized Linear Mixed Effects Models (LMEM, Baayen, Davidson, & Bates, 2008). RT data were modeled as a Gamma distribution with the identity link (Lo & Andrews, 2015), and accuracy data were modeled as a binomial distribution (logistic model). In all models, learning condition was included as a categorical variable, and relevant interactions between this factor and other predictors were included as noted below.

As a first step, *a priori* planned comparisons for the categorical variable of "group" (i.e., learning condition) consisted of (1) comparing the Typing to the Visual Condition (coding Typing as -1, Visual as +1, and Writing as 0), and (2) comparing the mean of the Typing and Visual Conditions to the Writing Condition (coding Typing and Visual as -1, and Writing as +2). This coding scheme has the benefit of providing orthogonal contrasts, and was used to test the hypothesis that any effects of learning condition stem from a difference between motor experience and non-motor experiences.

For any set of data where the first contrast returned a significant result (i.e., a significant difference between the Typing and Visual Conditions), then a second step was taken. Another LMEM l was run in order to report all pairwise comparisons. Specifically, this was achieved by re-fitting the LMEM from the first step, changing the contrasts for the variable "group" to a simple coding scheme, setting the Writing Condition as the baseline (first contrast: Typing coded as +2/3, Visual and Writing as -1/3; second contrast: Visual coded as +2/3, Typing and Writing as -1/3).

In all LMEMs, for both RT and accuracy analyses, p-values were obtained from bootstrapping (1,000 replications) the regression models, providing confidence intervals around the estimated beta-coefficients (Kuznetsova, Brockhoff, & Christensen, 2017). As a result, significance is reported as either $p < 0.001$, $p < 0.01$, $p < 0.05$, $p < 0.1$, or $p > 0.1$, reflecting whether the estimated coefficient fell outside of the 99.9% confidence interval, 99% confidence interval, and so forth. The random-effects included for each model were determined based on model comparisons of goodness-of-fit (chi-squared tests) based on backward testing procedures: a maximal random effects-structure was iteratively reduced, leaving only those which improved model fit in the final reported model (Baayen et al., 2008). The random-effects ultimately included in the best-fitting models are reported with the results in Chapters 3 and 4. Measures of variance explained are provided by the R package "MuMIn" (Bartón, 2018), giving both the amount of variance explained by the fixed-effects alone (marginal R^2) and the combination of the fixed- and random-effects together (conditional R^2).

Additional details, including the specific fixed-effects included to analyze each behavioral task, are reported below for each behavioral assessment (see section I. "Behavioral Methods").

Analyses of Learning Trajectory

Letter Recognition Task—In order to determine how quickly participants progressed on the letter recognition task, both accuracy and RT were analyzed. The fixed-effects include condition (Typing, T; Visual, V; Writing, W), % of training completed, trial order, and RT on previous trial, and the interaction of condition X % training completed. The terms of interest are the interaction terms, which reflect whether participants in one condition progressed more rapidly than another. It should be noted that, because participants were trained until reaching criteria (see section I. "Behavioral Methods"), any differences in rate of learning were driven by differences in the early sessions (i.e., all final assessments were near-ceiling performance).

Number of Training Sessions—As a more straight-forward measure of the rate of learning, a simple one-way ANOVA was conducted to assess differences in the mean number of training sessions required to reach criteria on the letter recognition task. Specifically, the dependent variable was the number of training sessions, with one between-participant variable being learning condition.

Analyses of Learning Generalization & Retention

Measures of how well the training tasks generalized to other letter processing tasks were drawn from: (1) the Letter Naming, (2) Writing Letters to Dictation, (3) Spelling Words to Dictation, (4) Reading Words, and (5) Novel Font Letter Recognition tasks. The measures of retention, collected at the follow-up time point, included: (1) Letter Recognition, (2) Letter Naming, and (3) Writing Letters to Dictation. All measures of generalization and retention were analyzed as described under "General Analysis Approach" with LMEM, and included the following fixed-effects as appropriate: trial order, RT on previous trial, and learning condition (Typing, T; Visual, V; Writing, W). Unless noted otherwise below, these were the only fixed-effects included for analyses of these tasks. For measures of retention, the actual number of days between the post-test and the follow-up were always included as well.

Spelling Words to Dictation—Additional variables included Word Length and Word Familiarity (i.e., whether the word was including during training).

Reading Words—Additional variables included word length and word familiarity (i.e., whether the word was during training). Because responses were scored in terms of the % of letters correct, each word's score was weighted as a series of binomial trials equal to its length (e.g., a 4-letter word scored as 50% correct was modeled as four trials, two 0's and two 1's).

Analysis of Same/Different Judgment Task

The Same/Different Judgement task is key for addressing questions related to the content of letter representations, and how these are affected by learning experiences. This task provides behavioral evidence of how letter perception is affected by learning experience, and reveals the multiple representations of letters, both sensory/motor and amodal. The basic assumption underlying the Same/Different Judgement task is that longer RTs to decide that two letters are different reflects greater similarity between those two letters. Therefore, differences in RT across responses to different pairs of letters are accounted for by simultaneous multiple regression, with predictors that index the similarity of pairs of letters along different dimensions (e.g., visual similarity, motoric similarity, etc.).

The pre and post training Arabic letter data sets were analyzed separately. The pre-training results were combined across participants in all learning conditions and analyzed to determine (1) which letter representations were perceived by and influenced performance for naïve observers, and (2) to verify that no significant differences existed between participants across the three learning conditions, prior to training. The post-training results were analyzed similarly, except the goal was to determine whether, after completing the training, there were any significant differences in letter perception attributable to the different learning conditions. Each learning condition was also analyzed individually at the post-test time point, in order to fully interpret any significant interaction terms.

Specifically, the dependent variable was RT in response to (correct) "different" judgments were analyzed with LMEM (following Wiley et al., 2016) . RT data were fit as a Gamma distribution (identity link) using generalized LMEM (see Lo & Andrews, 2015 for a similar approach to RT analysis). No analyses were conducted of accuracy due to near-ceiling performance at both time points (see Chapter 4). The following fixed-effects were included: learning condition (Typing, T; Visual, V; Writing, W), trial order, RT on previous trial, and 5 predictors of letter representational similarity: low and higher level visual representations (i.e., pixel overlap and visual feature similarity), motoric representation, phonological representations (letter name), and amodal representation (symbolic letter identities, SLIs). The five representational similarity measures were computed as follows:

Low Level Visual Representations (Pixel Overlap)—Each letter-shape was overlaid on each of the others, exactly as they were presented in the scanner, and the percentage of overlapping pixels was used, indexing a low-level, retinotopic measure of visual similarity.

Higher Level Visual Representations (Visual Features)—Following Wiley, et al., (2016), each letter-shape was decomposed into its constituent visual features (e.g., oriented lines, curves, intersections, terminations, etc..), and the similarity of each pair of letter-shapes on this dimension was calculated as the number of features in common, divided by the total number of features across the two letter-shapes.

Motoric Representations (Motor Bistrokes)—The same process used to computer visual feature similarity was used, except the constituent motor features used here were "bistroke" features, i.e., ordered pairs of strokes that indicate direction of motion. For example, the letter-shape "L" consists of just two strokes (downward and rightward), but these define a series of three ordered bistroke features: (1) initial-downward, (2) downward-rightward, and (3) rightward-final. The letter-shape "T" consists of four bistrokes: initial-downward,

downward-lift, lift-rightward, and rightward-final. The pair "L"-"T" thus shares two bistrokes (initial-downward and rightward-final) out of five, for a predicted similarity of 0.4.

Phonological Representations (Letter Names)—Replicating the methods used elsewhere (Rothlein & Rapp, 2017; Wiley, Wilson, & Rapp, 2016), letter name similarity was computed as the number of shared phonological features in the letter names. For example, the letter name for "B" consists of four features: for the consonant /b/: voiced, bilabial, stop, and the vowel /i/: close, central, unrounded. The letter name for "P" is the same except for the consonant being voiceless instead of voiced. The letter name similarity of the pair "B"-"P" is thus 0.83 (10 out of 12 features in common).

Amodal Representations: Symbolic Letter Identities (SLIs)—Each pair of letters were effects-coded as either +1 (same identity, i.e., allographs of the same letters) or -1 (different identity).

IV. Neuroimaging Analyses

The two neuroimaging tasks were used in tandem to investigate the neural activity in response to viewing Arabic letters. Briefly, the LLN (Letter Learning Network; see section II. "Neuroimaging Methods") task was used to localize regions of interest, specifically areas of cortex that showed significant changes in activity from pre- to post-training, selectively for Arabic letters. The results of the LLN analyses were, in turn, used to restrict the areas within which RSA was conducted as a searchlight analysis. The RSA approach was used specifically for data from the SDT (Symbol Detection Task) collected from the post-training MRI session. Given that the questions addressed by the RSA analysis depend upon how the learning conditions affected the letter representations, and in particular representations that require learning, the pre-training data are not presented in this dissertation.

Pre-processing of all MRI data was carried out in BrainVoyager QX 2.3 software (Maastricht, Netherlands). The participants' brains were aligned to AC-PC space within BrainVoyager, and then normalized to MNI common space using the SPM toolbox in MATLAB (Mat Works, Inc.). Details of the subsequent analyses are as follows.

Defining Regions of Interest

Using data from the LLN task, letter-learning regions were defined as those voxels (voxelwise FDR corrected $p < 0.05$) in which, based on the 2 pre-training and 2-post training runs of the SDT task, the following contrasts were significant: Arabic letters Post-Pre > Roman letters Post-Pre. In this way, the letter-learning regions of interest were defined as all voxels that showed experience- dependent changes in activity specifically related to Arabic letters.

The contrast used to determine the LLN did not include any voxels in the canonical VWFA region, which is known to be key to written language processing (parts of the fusiform and inferior occipital gyri, bilaterally; see Chapter 1). As will be discussed later (Chapter 4) this was presumably due to the high level of activation in this region of cortex at the pre-training time point, such that there was not a significant *increase* in activity across time points. To nonetheless identify this potentially relevant region, a separate contrast was used to identify letter-processing voxels within this region. Specifically, an anatomical ventral occipital-temporal (vOTC) mask was first applied to the concatenation of all four runs of the

LLN task (2 runs pre-training and 2 runs post-training). Then, within this anatomical mask, the contrast of Arabic letters > checkerboards (voxelwise FDR corrected $p < 0.05$) was used to identify relevant areas vOTC, and all RSA analyses conducted within the LLN were additionally conducted in this vOTC region.

RSA: Learning Experience Analyses

Representational similarity analysis (Kriegeskorte et al., 2008) treats the pattern of neural activity associated with experimental conditions as points in space across a span of voxels. The span of voxels under consideration may be of any shape and size of interest to the experimenter. More generally, the dependent measure in RSA is a dissimilarity measure that reflects differences in the neural response to different stimuli. It furthermore allows for investigating how these observed patterns of neuronal responses relate to hypothesized cognitive models, i.e., the expected patterns of responses given some predictive model. In the context of this dissertation, the patterns of activity in response to different Arabic letters is compared to the patterns that would be expected, if the underlying neural activity were reflecting information about the different sensory/motor and amodal representations. This is specifically implemented here by the use of LMEM regression, as described in detail below.

The 4 runs of Arabic letter from the Symbol Detection Task from the post-training time point were concatenated separately for each participant, and following pre-processing as described above, the beta values were extracted from all voxels within the regions of interest identified in both the LLN and vOTC. A searchlight method was then used (searchlight volume = 7 voxels) with the following steps: (1) For each participant, each searchlight volume yielded a 12x7 (letters X voxels) matrix of beta values; (2) These matrices were used to compute an observed neural similarity measure between each pair of letters, by calculating the (Euclidean) distance between the vector of beta values for each letter with every other letter (12 letters = 66 pairwise combinations); (3) This in turn resulted in a vector of length 66 for each participant (the neural similarity between each pair of letter-shapes) for each searchlight volume, and these were concatenated across-participants to provide the dependent measures for a LMEM analysis in each searchlight volume; (4) Using LMEM, multiple regression models were computed at each searchlight volume. The fixed effects were as follows:

Predictors 1-5—The predicted measures of similarity, which were the same 5 measures of letter representational similarity used to analyze RT in the Same/Different Judgement task: two measures of visual similarity (pixel overlap, and shared visual features), motoric similarity (shared motor features), letter name similarity (shared phonological features), and symbolic letter identity.

Predictor 6—A control variable to account for data artifacts that were not otherwise adjusted for in the pre-processing (e.g., motion artifacts, biorhythms). This control variable was calculated as follows: (1) A ventricle mask was construct for each participant. (2) Beta values for each letter-shape for each voxel within the ventricles were extracted. (3) An *observed* neural similarity measure was computed for each participant for each pair of letter-shapes, using the same method as already described, with the exception that the Euclidean distance was calculated across all voxels in the ventricle regions, instead of in 7 voxel searchlight volumes. This provided a measure of the neural similarity of the letter-shapes entirely unrelated to any functional neural activity or cognitive processing (given the nature of activity that is recorded from within the ventricles). Including these measures as a control predictor allows for statistical control of some amount of observed, neural similarity that is in fact explained by activity in the ventricles and thus, not due to representational similarity of the letters in any cognitive dimension[10].

Predictor 7—Condition (Typing, T; Visual, V; Writing, W) was included as a main effect. All pairwise comparisons were computed: Typing versus Visual (TvV), Typing versus Writing (TvW), and Visual versus Writing (VvW)[11].

Predictors 8-17: The interaction terms between each of the 5 predicted similarity measures on the one hand, and the pairwise contrasts between the learning conditions. For example, a beta-value and p-value was computed for the interaction of Motoric Similarity X Condition (TvV), reflecting a difference in the association between observed neural similarity and predicted motoric similar for participants in the Typing Condition, relative to the Visual Condition.

The LMEM analyses thereby provide, for each searchlight volume, beta values indicating the direction and magnitude of the relationship between neural similarity and predicted similarity measures. This includes both main effects (i.e., on average across all three learning conditions) and interactions between learning conditions**. These are termed**

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[10] The control predictor was seen to relate positively with neural similarity, significantly so in many voxels, suggesting that indeed some amount of variance in the observed patterns of neural similarity is due to un-accounted for factors relating to data artifacts such as motion and biorhythms.
[11] Given a categorical variable with 3 levels, necessarily only two contrasts can be computed within a single regression model. Therefore, each LMEM at each searchlight volume was in fact computed twice, changing the contrasts from the first to the second iteration, in order to provide p-values for each of the three pairwise contrasts.

"Learning Experience Analyses", as they reveal information about the differences across learning conditions. Given the *a priori* expectation that there would be significant differences in the patterns of activity across learning experiences, each group (T, V, W), was also analyzed individually, in order to provide additional information for interpreting significant interactions. For example, finding a significant interaction of Motoric Similarity X Group (TvV), indicates that the relationship between neural similarity and motoric similarity was significantly different for those who learned by typing compared to those who learned by visual study. By also assessing the two groups separately, it is possible to determine the source of the interaction. For example, it could be due to both groups showing a significant effect of Motoric Similarity that was stronger for one group, or due to only one group showing a significant effect, or to the groups showing effects in the opposite direction, etc.

Finally, to address the issue of multiple comparisons in the searchlight method (4,535 voxels were included in the LLN and an additional 1,766 in the vOTC regions), a cluster size threshold correction was used. Specifically, a voxelwise uncorrected (i.e., primary threshold) $p < 0.005$ was used, and the BrainVoyager Cluster-Level Statistical Threshold Estimator plugin was then applied to determine the minimum number of contiguous voxels needed to constitute a significant cluster, at $p < 0.05$.

RSA: Behavioral Performance Analyses

The same approach used to analyze the relationship between learning conditions and letter representation types (i.e., the Learning Experience Analyses) was also used to assess whether there were differences in representational similarity across participants that was related to their behavioral performance**—thus these are termed "Behavioral Performance Analyses"**. In other words, whereas the Learning Experience Analyses provide information as to how letter representations differed as a consequence of learning condition, the Behavioral Performance Analyses give an indication as to how the letter representations were implicated in letter processing tasks. For example, the Learning Experience Analyses could reveal a cluster of voxels sensitive to visual letter representations in the occipital lobe, and that this pattern of activity was unique to participants in the visual learning condition. The Behavioral Performance Analyses could further reveal that participants who were more accurate at letter recognition were also those who showed the strongest visual letter representations in those voxels. Taken together, then, those hypothetical results would suggest not only that the visual learning condition was associated with stronger visual representations in a particular brain region, but that there was furthermore an association between that type of representation in that area and successful letter recognition performance.

Specifically, four measures of behavioral performance were tested, all based on the post-training time point: RT on the Letter Recognition task, RT on the Letter Naming task, accuracy on the Writing Letters to Dictation task, and accuracy on the Reading Words task. RT instead of accuracy was chosen for the Letter Recognition and Letter Naming tasks, because there was relatively little variance on those tasks in terms of accuracy (and in fact, accuracy was near ceiling on those tasks for the 12 letter-shapes included in the neuroimaging task). Four additional LMEM were computed in each searchlight volume, identical to the ones described for the RSA Learning Experience Analyses, except in place of the group categorical variable there was a continuous measure of behavioral performance.

V. Primary Aims

As a summary of this chapter, each of the primary questions of the dissertation are revisited here, in terms of how the methods and analyses allow for those questions to be addressed. There are elements of the experimental design itself, as well as the data analysis approach, contribute to evaluating whether writing experience may be more beneficial for letter learning than non-motor experience (see Chapter 1), to addressing shortcomings in the existing literature, and ultimately to answering these three questions:

Question 1: Are the effects of writing experience due to motor learning *per se*, or to other variables confounded with the writing experience?

This question is addressed by the experimental design itself, which was developed to directly rule out a number of potential confounding variables that otherwise leave open the possibility that effects of the learning conditions are unrelated to the motor or non-motor nature of the experience. Specifically, the following elements of the experimental design address the following issues: (1) <u>Selective rehearsal displacement</u>: the study was conducted as a between-participants design to rule out the possibility that within-participant designs may give a benefit to letters learned by writing, relative to letters learned by non-motor experience because of lower performance on the latter. (2) <u>Variability of input</u>: multiple fonts were presented to participants in all conditions in order to reduce the likelihood that writing experience influences letter learning only because typing and visual learning conditions provide no variability in exemplars for learning. (3) To address the possibility that writing experience is beneficial because of visual learning from *observing* the strokes used to write letters, as opposed to motor learning from *producing* those strokes, animated videos of the letters being written were presented to participants in all conditions.

Question 2: Does writing experience recruit only sensory/motor representations?

The use of two techniques that provide information about the content of the letter representations, the LMEM analysis of the Same/Different Judgment task and the RSA "Learning Experience Analyses", are key to addressing this question. They do so by revealing the types of representations (in behavior or neural activity) that are associated with each of the learning conditions. Any evidence for SLI representation is particularly important for determining whether the effects of writing experience involve recruiting amodal letter representations.

Question 3: Which types of representations, motoric or otherwise, underlie the behavioral benefits of writing experience?

The final question is addressed by the RSA "Behavioral Performance Analyses", as they in particular examine how patterns of neural activity relate to performance on the behavioral tasks. The four behavioral measures which were included as interaction terms in the RSA were: the RT on letter recognition, the RT on letter naming, the accuracy on spelling words to dictation, and the accuracy on word reading. The logic is again as follows: whereas the “Learning Experience Analyses” provide information about the types of letter representations that are associated with patterns neural activity generally, *and whether this differs as a consequence of learning condition*, the “Behavioral Performance Analyses” evaluate how the letter representations differ according to individual differences in the participants’ abilities on assessment tasks. In this way, these analyses provide an opportunity to identify: (1) clusters of activity corresponding to certain types of letter representations, (2) how the representations in those clusters are affected by learning condition, and (3) how those various representation are associated with specific behavioral measures (e.g., fast letter recognition, poor spelling performance, etc).

Chapter 3 – Results: Learning Letters

This chapter reports the results of the analyses of behavioral tasks administered over the course of the longitudinal training study (see Chapter 2, section I. "Behavioral Methods"). These results are most relevant to answering the first of the three major questions addressed in the dissertation: Are the effects of writing experience due to motor learning *per se*, or to other variables confounded with the writing experience? The analyses first evaluate the effects, if any, of the writing experience on letter learning.

To briefly review: Chapter 1 described how a number of studies have indicated that learning letters via writing experience, as opposed to non-motor experiences, provides behavioral benefits for certain letter processing tasks. In addition, other studies have reported that sensory/motor cortex activates in response to passive letter viewing, but only among observers who have had writing experience. These two basic results have been taken together as evidence for a strong embodied cognition claim that letter representations reduce to sensory/motor representations. However, a number of unresolved issues call into question how much the current findings actually support theories or grounded cognition more generally. Some grounded cognition views allow non-sensory/motor representations, but nonetheless claim that sensory/motor representations are fundamental for all conceptual representations, both concrete and abstract, and are skeptical as to the existence of amodal representations. The assumptions necessary in order to claim that the writing experience/letter learning evidence supports grounded cognition theories can be characterized as follows: (1) that the behavioral effects of writing experience stem from the writing process itself, and not incidental factors related to the experimental conditions; (2)

that motoric, not amodal, letter representations are recruited during letter perception; and (3) that there is a causal link between the motoric representations, on the one hand, and the behavioral effects of writing experience, on the other.

The results of this chapter test in particular the first assumption described above, and contribute to testing the second and third assumptions in tandem with additional evidence reported in Chapter 4. The details of the methods and analyses are in Chapter 2, including the general approach to analysis (III. "Behavioral Analyses", section "Linear Mixed Effects Models: General Analysis Approach"). This chapter is divided into three main sections, one each for: learning trajectory, generalization of learning, and retention of learning. Each of these sections concludes with interim discussion of the results. A final section summarizes how letter learning was affected, in terms of behavioral outcomes, by the three different learning conditions.

Demographics

In total, 42 participants enrolled in the training study, 27 of whom were also enrolled in the neuroimaging sessions. 36 participants completed the training study through the post-training time point assessments, 33 of whom returned for a follow-up session approximately one month later. Of the 27 participants enrolled in the neuroimaging, 24 completed both pre- and post-training scans. Basic demographics of the participants, with enrollment numbers per learning condition, are reported in Table 3-1. All participants were native English speakers, with no previous knowledge of Arabic or any language written in the Arabic alphabet (e.g., Persian, Urdu). All participants signed informed consent according to Johns

Hopkins IRB protocols. All participants were paid $10 per behavioral session (including pre-training assessments), and received a $10 bonus for returning for the one-month follow-up. Individuals who participated in neuroimaging sessions received $50 in compensation per scan. Participants who completed the follow-up session additionally completed a debriefing questionnaire (see Appendix X).

Table 3-1. Participant demographics. T = Typing, V = Visual, W = Writing.

Learning experience	Enrolled *(female)*	Age *(sd)*	Education *(sd)*	Completed post-tests	Completed follow-up
T	*14 (11)*	21.7 *(2.6)*	15.8 *(1.4)*	12	11
V	14 *(10)*	21.1 *(4.6)*	15.2 (*1.8)*	12	10
W	14 *(11)*	21.6 *(3.1)*	15.8 *(2.2)*	12	12

I. Learning Trajectory

Two analyses, (1) Time to Reach Criterion and (2) Training Trajectory, were conducted to assess the rate at which participants progressed on their letter recognition ability, and whether this rate differed depending on the learning condition. A third analysis, (3) Post-training Letter Recognition, assesses performance across the learning conditions, upon reaching the training criteria. These three analyses were conducted on data from the Letter Recognition Task that consisted of a 4AFC test, with an auditory cue of the letter name and visually similar letter distractors; the details can be found in Chapter 2 (I. "Behavioral Methods", section "Behavioral Assessments"). Also, the details of these analyses can be found in Chapter 2 (II. "Behavioral Analyses", section "Analyses of Learning Trajectory").

1. Time to Reach Criterion

Figure 3-1 reports the time to reach criteria, measured in terms of the number of training sessions, for each learning condition. On average, participants in the Writing condition required the least amount of training (W, 3.67 sessions), followed by the typing (T, 3.92) and Visual Conditions (V, 4.25). However, a one-way ANOVA of the effect of group (T, V, or W) revealed no significant effect, $F(2, 33) = 0.63$, $p = 0.54$.

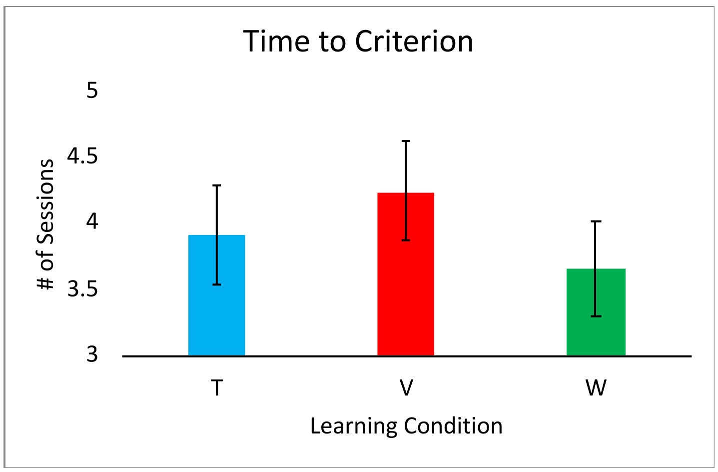

Figure 3-1. Time to reach criteria on letter recognition task. T = Typing, V = Visual, W = Writing.

2. Training Trajectory

To get a finer-grained measure of the learning, the results of LMEM analyses of the Letter Recognition Task administered throughout the course of training are reported in Table 3-2, and the main predictors of interest are depicted in Figure 3-2, showing the LMEM predicted accuracy and RT (y-axes), respectively, as a function of the percentage of training completed (x-axis) for each of the learning conditions.

The results reveal that the rate of improvement in accuracy (Table 3-2, Figure 3-2 left panel) was significantly slower for the Visual Condition compared to both Typing ($p = 0.01$) and Writing ($p = 0.02$), with no significant difference between Typing and Writing ($p = 0.61$). In terms of RT (Table 3-2, Figure 3-2 right panel), there was a significant main effect of Condition: on average across training, the Typing Condition was slower on letter recognition compared to the Writing Condition ($p < 0.001$), which was slower compared to the Visual Condition ($p < 0.001$). In contrast, the *rate* of improvement in RT was slower for in the Writing Condition compared to the Visual Condition ($p < 0.001$), which in turn was slower than the Typing Condition ($p < 0.001$).

Table 3-2. LMEM of the rate of improvement on the letter recognition task over the course of training, for accuracy (left panel) and RT (right panel). Random effects included intercept and slope for trial order and % training, by-participants, and intercept and Condition, by-items. T = Typing, V = Visual, W = Writing. *** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1.

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	2.19177	0.25027	8.758	<0.001	***
TvW	-0.13663	0.4144	-0.33	0.7416	
VvW	0.22788	0.42796	0.532	0.5944	
TvV	0.18226	0.21787	0.837	0.40285	
% training	1.32352	0.08325	15.898	<0.001	***
trial order	0.15364	0.03268	4.701	<0.001	***
TvW:% training	0.08366	0.16332	0.512	6.09E-01	
VvW:% training	-0.36792	0.1628	-2.26	0.0238	*
TvV:% training	-0.22578	0.08339	-2.707	0.00678	**
	marginal R^2		conditional R^2		
	0.2385159		0.5690961		

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	2505.233	2.306	1086.3	<0.001	***
TvW	-213.652	2.214	-96.5	<0.001	***
VvW	306.193	4.322	70.8	<0.001	***
TvV	-121.184	2.777	-43.6	<0.001	***
% training	-164.009	2.667	-61.5	<0.001	***
trial order	-39.241	2.111	-18.6	<0.001	***
previous trial RT	117.883	2.176	54.2	<0.001	***
TvW:% training	13.914	2.467	5.6	<0.001	***
VvW:% training	-86.683	2.94	-29.5	<0.001	***
TvV:% training	-58.867	2.236	-26.3	<0.001	***
	R^2				
	0.4339036				

Figure 3-2. Rate of improvement on the Letter Recognition task over the course of training, depicted as predicted responses from the LMEM analyses of accuracy (y-axis, left panel) and RT (y-axis, right panel) across the percentage of training completed (x-axis). T = Typing, V = Visual, W = Writing.

3. Post-training Letter Recognition

The post-training letter recognition task evaluated letter recognition ability at the end of training for the three learning conditions. The Letter Recognition Task was administered at the beginning of the post-training session, which itself took place 2-5 days after participants reached >90% accuracy and >25% reduction in RT on the task.

The average accuracy and RT by learning condition are depicted in Figure 3-3 (left and right panels, respectively), with the results of the LMEM analysis in Table 3-3. For accuracy, the analysis verifies that after reaching criteria, there was no significant difference between learning conditions (Table 3-3, Figure 3-3 left panel), with all groups achieving high accuracy (96%, 95%, and 97% respectively for T, V, and W). For RT (Table 3-3, Figure 3-3 right panel), there was a significant main effect of group, with the average RT on letter recognition for those in the Typing Condition (2130ms) significantly slower than in the Visual Condition (1892ms), which in turn was significantly slower than in the Writing Condition (1795ms). Despite this main effect of group, it should be noted that the improvement in RT across training sessions was significant across the three learning conditions (Table 3-2 right panel, effect of "% training completed", $p < 0.001$).

Table 3-3. LMEM of the post-training Letter Recognition task, for accuracy (left panel) and RT (right panel). Random effects included intercept and slope for trial order and % training, by-participants, and intercept and Condition, by-items. T = Typing, V = Visual, W = Writing. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$.

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	4.08154	0.26109	15.633	< 0.001	***
TvV	0.05232	0.23466	0.223	0.82356	
(T+V)vW	0.16616	0.14026	1.185	0.23614	
trial order	0.30678	0.09791	3.133	0.00173	**
	marginal R^2		conditional R^2		
	0.02862526		0.37861818		

Fixed effects:	Estim	Std.	z-value	Pr(>|z|)	
(Intercept)	2386	19	123.24	< 0.001	***
TvV	362	12	31.4	< 0.001	***
TvW	322	5	62.6	< 0.001	***
VvW	141	6	23.3	< 0.001	***
trial order	-105	14	-7.41	< 0.001	***
previous trial	7.43	9	0.84	0.403	
	R^2				
	0.43				

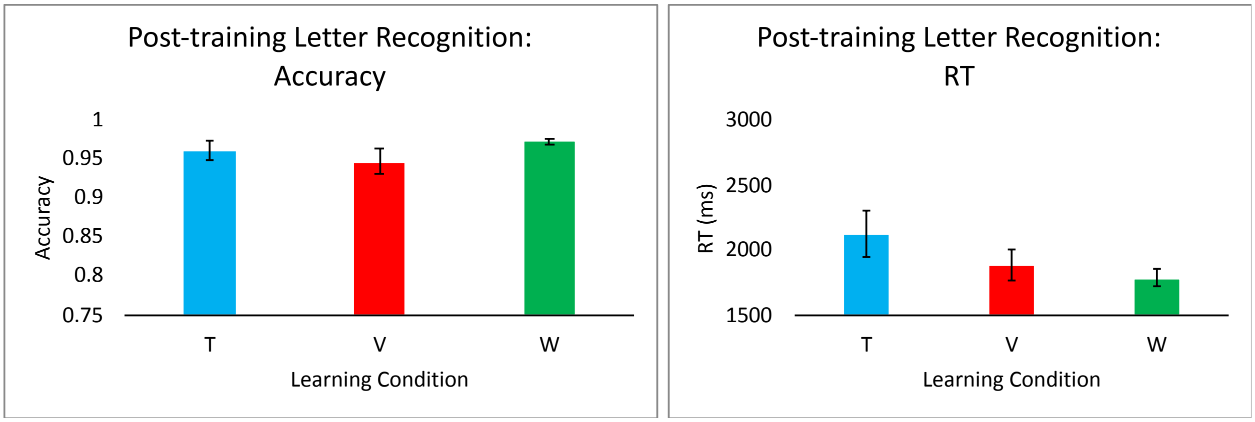

Figure 3-3. Grand mean of accuracy (left panel) and RT (right panel) by Condition on the post-training time point Letter Recognition task. Error bars reflect standard error of the mean. T = Typing, V = Visual, W = Writing.

Discussion: Learning Trajectory

In terms of the learning trajectory, the results were mixed. The critical condition of interest, the Writing Condition, resulted in performance that was in between the Typing and Visual Conditions in terms of the rate of improvement on letter recognition, for both RT and accuracy. The results reveal the following patterns: (1) in terms of letter recognition accuracy, typing training resulted in the worst initial performance, but subsequently showed the greatest improvement, ultimately allowing participants in that condition to catch up to the other two in terms of letter recognition accuracy; (2) visual training resulted in the best initial performance, both RT and accuracy, but progress was subsequently slower, and thus participants in that condition ultimately required more time to reach criteria; (3) writing training resulted in performance in between that of the other two conditions, with the total amount of time to reach criteria being the shortest. Importantly, on the post-training letter recognition task, all participants performed at a high level of accuracy on letter recognition, with no significant differences across conditions. However, participants trained by writing were significantly faster than participants in the other two conditions at the post-training time point. This is particularly striking given that those writing participants received *less* training on average, as they were fastest to reach criteria.

The pattern of results reveals different learning trajectories as a consequence of the training tasks, and upon close inspection, a nuanced answer to the question of whether one learning experience is more beneficial than the others. Clearly, if only one hour of training were available, the visual study condition would be preferable: both initial speed and accuracy were best in this condition. However, the Typing and Writing conditions had significantly faster rates of improvement on letter recognition, and ultimately required less time to reach criteria. This may stem from the degree of "desirable difficulty" of these two training tasks (Bjork, 1994; McDaniel & Einstein, 2005). Briefly, the notion is that certain difficulties that "slow the apparent rate of acquisition can enhance post-instruction recall and transfer" (Bjork, 2013). The tasks demands of the Typing and Writing Conditions, while apparently slowing the initial acquisition of letter recognition, may introduce a degree of desirable difficulty into the learning process. Under such an account, the slower improvement of the Visual Condition after the first session was due to weaker retention from one session to the next, whereas the other learning conditions were relatively better at supporting retention. In other words, more "relearning" across training sessions may have been needed in the Visual Condition relative to the other two, and thus an apparent initial advantage (i.e., after one hour of training) was attenuated with repeated practice. That the visual training task was easier (as measured by amount of time spent to complete the probe/target task, as well as accuracy on this task; see Appendix C) supports this conclusion. The concept of desirable difficulty relates not only to retention but also to generalization (i.e., transfer), and thus will be returned to in the next section in the discussion of how well training generalized across tasks.

II. Generalization of Learning

This section reports on the analyses of how well the training generalized to other letter processing tasks besides letter recognition, and whether generalization was affected by the learning condition. To address these questions, we consider the results of five tasks on which the participants were *not* trained and/or never received feedback. All of these were administered after the participants had reached criteria on letter recognition, either at the post-training or follow-up time point. These tasks are reported in order of increasing generalization, i.e., beginning with the task that was most similar to the letter recognition task.

1. Novel Font Letter Recognition

Although this task was only administered at the follow-up time point, it serves as a measure of generalization because it tested the participants' ability to recognize the trained letters in fonts they had never been exposed to previously. The descriptive statistics are depicted in the left panel of Figure 3-4 and the LMEM analysis is reported in the left panel of Table 3-4. The fonts tested in this task are pictured in Figure 2-5 (and can be compared with the trained fonts in Figure 2-2).

There were no effects of learning condition on accuracy, with similar letter recognition for each condition, although writing training trended to result in the highest accuracy (82%, 83%, and 88%, respectively for T, V, and W). However, there was a significant effect of learning condition on RT (Table 3-4, Figure 3-4 right panel), with the Writing Condition leading to the fastest RT (2437ms), significantly faster than the Visual Condition (2528ms, $p < 0.001$), which in turn was significantly faster than the Typing Condition (2927ms, $p < 0.001$).

Table 3-4. LMEM of performance on the Novel Font Letter Recognition task, for accuracy (left panel) and RT (right panel). Random effects included intercept and slope for trial order, by-participants, and intercept and Condition, by-items. T = Typing, V = Visual, W = Writing. *** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1.

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	2.229386	0.199367	11.182	<2e-16	***
days since post-test	-0.296777	0.171767	-1.728	0.084	.
TvV	0.073698	0.210082	0.351	0.726	
(T+V)vW	0.101419	0.118225	0.858	0.391	
trial order	0.004255	0.079172	0.054	0.957	
	marginal R^2		conditional R^2		
	0.02489694		0.38061464		

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	2907.452	10.407	279.36	<2e-16	***
days since post-test	5.772	10.768	0.54	0.5919	
TvV	224.474	24.156	-9.29	<2e-16	***
TvW	268.427	15.892	16.89	<2e-16	***
VvW	43.951	13.435	3.27	1.07E-03	**
trial order	-24.19	13.709	-1.76	0.0776	.
previous trial RT	66.966	12.259	5.46	4.69E-08	***
	R^2				
	0.3552435				

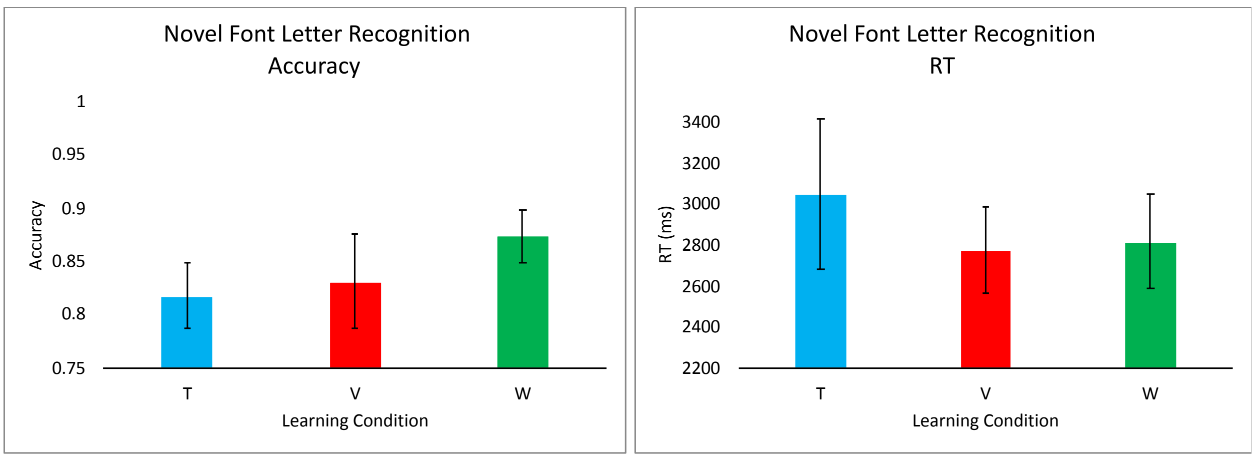

Figure 3-4. Grand mean of accuracy (left panel) and RT (right panel) by Condition on the follow-up, Novel Font Letter Recognition task. Error bars reflect standard error of the mean. T = Typing, V = Visual, W = Writing.

2. Writing Letters to Dictation

The descriptive statistics for the Writing Letters to Dictation task are reported in Figure 3-5 and the LMEM analysis in Table 3-5. This task was administered at both the post-training and follow-up time points; here, only the post-training results are reported, as the follow-up results constitute one of the analyses of learning retention (reported in section II of this chapter). This task differed from the writing task that was used during training for the Writing Condition, in that in this instance there were no visual stimuli presented, and thus the letters had to be drawn from memory. The participants were reminded that most letters had 2 allographs, and were prompted to write both of them if they could recall them.

There was a significant effect of learning condition: specifically, the Writing Condition resulted in better performance compared to both the Typing ($p = 0.02$) and Visual ($p < 0.001$) Conditions, with the Typing Condition marginally outperforming the Visual Condition ($p = 0.07$). An analysis of the errors revealed that mirror-reversals were the most common error type and, in fact, participants in both the Typing (5% of responses) and Visual (11% of responses) cConditions were more likely to produce these errors than those in the Writing Condition (2% of responses), a significant difference by LMEM analysis ($p < 0.01$).

Table 3-5. LMEM of performance on Writing Letters to Dictation at the post-training time point (left panel) and follow-up (right panel). Random effects included intercept, by-participants, and intercept and Condition, by-items. T = Typing, V = Visual, W = Writing. *** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1.

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	1.6373	0.1905	8.593	<2.00E-16	***
TvV	-0.78	0.4274	-1.825	0.067991	.
TvW	-1.0531	0.4505	-2.338	0.0194	*
VvW	-1.8335	0.4458	-4.113	3.91E-05	***
	marginal R^2		conditional R^2		
	0.1174106		0.2996246		

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	-0.1281	0.1722	-0.744	0.4571	
days since post-test	-0.2815	0.1707	-1.649	0.0991	.
TvV	-0.1161	0.2064	-0.562	0.574	
(T+V)vW	0.1306	0.1198	1.09	0.2757	
	marginal R^2		conditional R^2		
	0.03469425		0.20871945		

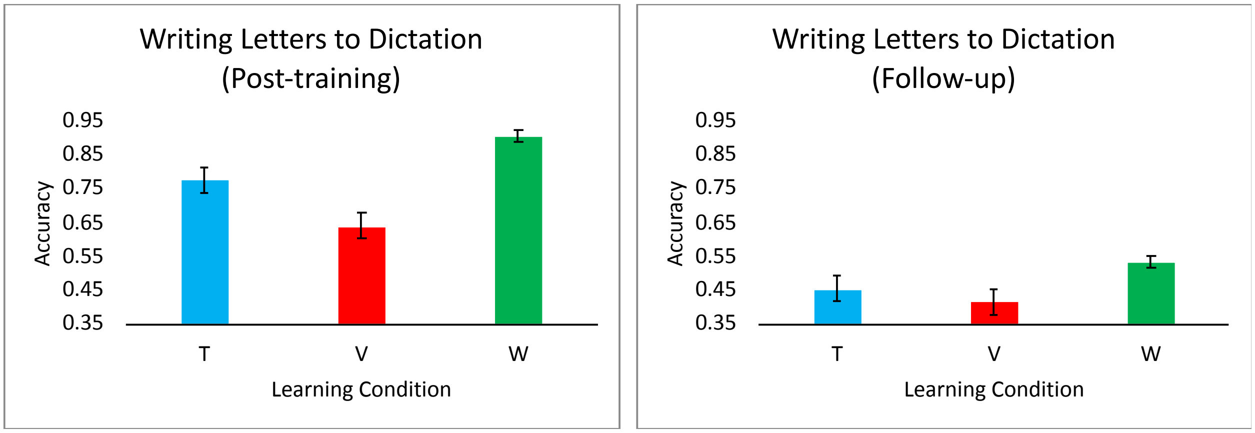

Figure 3-5. Grand mean of accuracy for Writing Letters to Dictation at the post-training (left panel) and follow-up (right panel) time points, by Condition. Error bars reflect standard error of the mean. T = Typing, V = Visual, W = Writing.

3. Spelling Words to Dictation

The descriptive statistics for the Spelling Words to Dictation task are reported in Figure 3-6 and the LMEM analysis in Table 3-6. On this task, the writing and Visual Conditions resulted in similar performance (76% and 72%, respectively, $p = 0.84$), whereas the Typing Condition resulted in the worst performance (63% mean accuracy), on average producing significantly fewer correct letters compared to both the Visual ($p = 0.02$) and Writing ($p = 0.03$) Conditions.

Table 3-6. LMEM of performance on Spelling Words to Dictation at the post-training time point. Random effects included intercept and slope for length, by-participants, and intercept and Condition, by-items. T = Typing, V = Visual, W = Writing. *** p < 0.001, **e p < 0.01, * p < 0.05, . p < 0.1.

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	1.18695	0.2541	4.671	2.99E-06	***
TvV	0.52607	0.23022	2.285	0.0223	*
TvW	-0.95246	0.43824	-2.173	0.0298	*
VvW	0.09969	0.47871	0.208	0.835	
word length	-0.28692	0.1695	-1.693	0.0905	.
training word	0.02394	0.17824	0.134	0.8932	
	marginal R^2		conditional R^2		
	0.06018077		0.38123567		

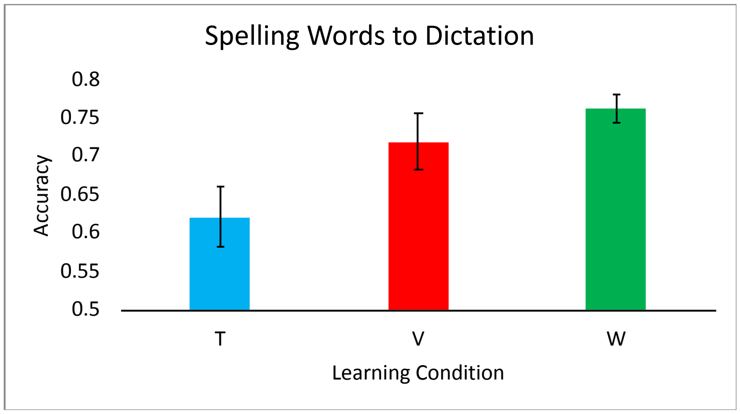

Figure 3-6. Grand mean of accuracy for Spelling Words to Dictation at the post-training time point, by Condition. Error bars reflect standard error of the mean. T = Typing, V = Visual, W = Writing.

4. Letter Naming

The descriptive statistics for the Letter Naming task are reported in Figure 3-7 and the LMEM analysis in Table 3-7. For accuracy (left panels), there was a significant effect of learning Condition, reflecting the fact that the Writing Condition resulted in the highest accuracy in letter naming (mean accuracy 93%), significantly higher than the Typing (mean accuracy 86%) and Visual (mean accuracy 83%) Conditions, $p = 0.04$. There was no significant difference between the Typing and Visual Conditions ($p = 0.46$). For RT (right panels), there was no significant difference across conditions, although the Writing Condition tended to be the fastest (mean RT of 1489ms, 1346ms, and 1263ms, respectively for T, V, and W).

Table 3-7. LMEM of performance on Letter Naming at the post-training time point. Random effects included intercept and slope for trial order, by-participants, and intercept and Condition, by-items. T = Typing, V = Visual, W = Writing. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$.

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	3.042954	0.332778	9.144	<2.00E-16	***
TvV	-0.22977	0.310516	-0.74	0.4593	
(T+V)vW	0.419652	0.204529	2.052	0.0402	*
trial order	-0.00241	0.068357	-0.035	0.9719	
	marginal R^2		conditional R^2		
	0.053043		0.54896515		

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	1636.134	104.699	15.627	<2.00E-16	***
TvV	-68.773	48.172	-1.428	0.1534	
(T+V)vW	-30.146	41.784	-0.721	0.4706	
trial order	-8.565	13.334	-0.642	0.5206	
previous trial RT	28.131	12.78	2.201	0.0277	*
	R^2				
	0.3748489				

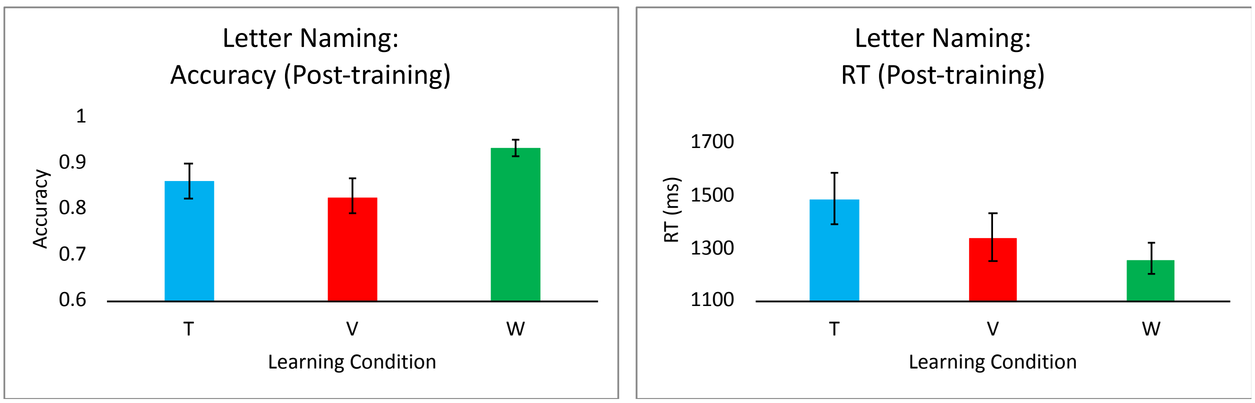

Figure 3-7. Grand mean of accuracy (left panel) and RT (right panel) for the Letter Naming task at the post-training time point, by Condition. Error bars reflect standard error of the mean. T = Typing, V = Visual, W = Writing.

5. Reading Words

The descriptive statistics for the reading words task are reported in Figure 3-8 and the LMEM analysis in Table 3-8. There was a significant effect of word length ($p < 0.05$) such that more errors were made on longer words. There was no significant difference between the familiar words (i.e., those presented during the training blocks) and the novel words ($p > 0.1$). Although accuracy was highest for the Writing Condition, there was no significant difference across learning Conditions (all p's > 0.1). There was a significant interaction of the length effect with the learning Conditions. Specifically, the length effect was significantly larger for the Typing Condition compared to the Writing Condition ($p < 0.05$) and marginally larger compared to the Visual Condition ($p = 0.056$), with no difference between the Visual and Writing Conditions ($p > 0.10$). Separate analyses of the effect of length by Condition revealed that the length effect was only significant for the Typing Condition ($p < 0.01$), not for the visual or Writing Conditions (p's > 0.1). The effect sizes reveal that the predicted decrease in accuracy for a 6-letter word relative to a 2-letter word was 50% for the Typing Condition, versus just 23% and 16% for the Visual and Writing Conditions.

Table 3-8. LMEM of performance on Reading Words task at the post-training time point. Random effects included intercept and slope for length, by-participants, and intercept by-items. T = Typing, V = Visual, W = Writing. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$.

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	0.28319	0.35247	0.803	0.4217	
TvV	0.2668	0.39669	0.673	0.5012	
TvW	-0.98203	0.78925	-1.244	0.2134	
VvW	-0.44842	0.77432	-0.579	0.5625	
Length	-0.35333	0.1417	-2.493	0.0127	*
Familiar	0.03612	0.27514	0.131	0.8956	
TvV:Length	0.17308	0.09038	1.915	0.0555	.
TvW:Length	-0.4558	0.17898	-2.547	0.0109	*
VvW:Length	-0.10965	0.17341	-0.632	0.5272	
	marginal R^2		conditional R^2		
	0.0434294		0.55114612		

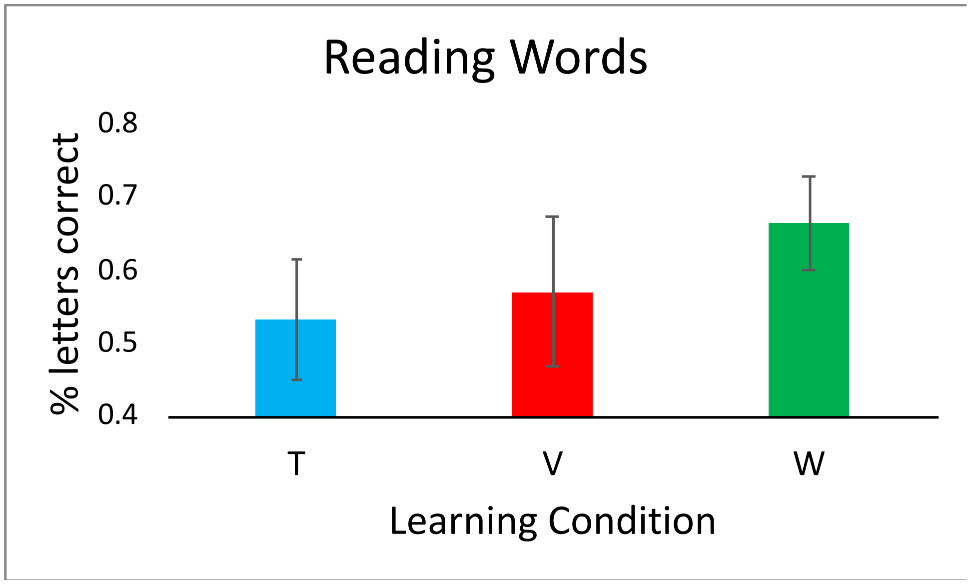

Figure 3-8. Grand mean of accuracy (% letters correct) for post-training time point Reading Words task, by Condition. Error bars reflect standard error of the mean. T = Typing, V = Visual, W = Writing.

Discussion: Generalization of Learning

A summary of the generalization analyses is presented in Table 3-9. Overall, the writing training task resulted in the strongest generalization to other, untrained, letter processing tasks. The participants trained in the Writing Condition performed significantly better than both those in the typing and Visual Conditions on three measures: (1) RT to recognize letters in novel fonts, (2) accuracy in writing letters to dictation, and (3) accuracy in naming letters. The writing-trained participants and visual-trained participants both significantly outperformed the typing-trained participants on spelling words to dictation and word reading (as evidenced by a significantly smaller word length effect). This pattern of results can also be described as the typing training supporting the worst generalization, as it did not result in significantly better performance compared to any other condition, on any measure. For their part, participants who had the visual study training task were in the middle, being significantly outperformed by the participants in the Writing Condition on three measures, but themselves significantly outperforming those in the typing training on three measures.

Table 3-9. Summary of the generalization of learning results, ranking the learning Conditions from best (1) to worst (3) performance. Highlighting reveals significant comparisons: gold = best/tied for best; silver = second best/tied for second best; bronze = worst performance. Cells without highlighting reflects no significant differences.. T = Typing, V = Visual, W = Writing.

Generalization	T	V	W
Novel Font Acc.	3	2	1
Novel Font RT	3	2	1
Writing	2	3	1
Spelling	3	2	1
Naming Acc.	2	3	1
Naming RT	3	2	1
Reading Acc.	3	2	1
Reading Length Effect	3	2	1

The results of the measures of generalization are consistent with claims that writing experience provides benefits to letter learning, not seen with non-motor learning experiences like typing or visual study. Numerically, participants with writing experience performed the best on *every* measure of generalization, significantly better than those with typing experience on five tasks, and visual experience on three tasks.

What insight do the results of the dissertation thus far provide into the nature of this apparent benefit of writing experience for learning letters? The main contribution of the dissertation is to provide insight into the content of letter representations, which have implications for the debate between grounded cognition and abstractionism. However, it must first be established that there are significant effects of motor experience. This discussion therefore first returns to four accounts that were outlined in Chapter 1 (sections IV-VI), which provide explanations of letter learning benefits from the motor condition that appeal to factors other than the motor experience itself. .

(1) Variable visual input—Although this concern was addressed here by presenting multiple fonts to participants in all three learning conditions, the novel font letter recognition task has bearing on this hypothesis because it tested the ability to recognize letters despite novel variation in their shapes. In this way it tests whether the perceptual letter categories differ across the learning conditions. While there were no differences in terms of accuracy on this task, the Writing Condition did result in significantly faster RT than the Visual Condition, which was in turn faster than the Typing Condition. The superior performance of the Writing Condition could possibly be attributed to additional variability of input from each participant's own writing, above and beyond the multiple fonts that were presented, but then an explanation is needed as to why the Visual Condition outperformed the Typing Condition.

(2) An effort account—The benefits of writing experience could potentially be attributed to training conditions which require more effort, or relatedly that provide more exposure to the stimuli, compared to other conditions (see Chapter 1, section IV, 24). However, it was shown in the previous section on the learning trajectory, that the typing training task required the most time to complete, and was the most challenging (as reflected by higher error rates in finding the correct keys on the keyboard, compared to completing the visual training task). Additionally, participants in the Writing Condition most quickly reached criteria, and thus -on average- participants in that condition had the least amount of exposure to the letter stimuli. Therefore, a simple effort account is a poor explanation for the better generalization to various letter processing tasks, among participants in the Writing Condition—indeed, the effort account would seem to make precisely the wrong prediction of superior performance in the Typing Condition--which showed the poorest generalization--and the worst performance in the Visual Condition--which mostly outperformed the Typing Condition.

(3) Transfer appropriate processing—The transfer appropriate processing account can fairly readily explain the findings of the writing letters to dictation task, given that this task was clearly most similar to the writing training task (the difference being that the generalization task required producing the shapes from memory, rather than by copying). Even so, the results provide insight into the nature of how writing experience benefits the ability to recall the shapes from memory and produce them by hand, because the Writing Condition outperformed the other conditions in a specific way: the result was largely driven by the high rate of *mirror-reversal errors* made by participants in the typing and especially the Visual Conditions. This suggests that one aspect of letter learning that is particularly supported by writing experience is the breaking of mirror invariance; this point is expanded upon in the discussion of the retention results (section III). More importantly, apart from the writing letters to dictation task, a transfer appropriate processing account does not readily explain the rest of the generalization results. Arguably the two results that are most problematic for this are the letter naming task, where writing training resulted in significantly better accuracy than either of the other conditions, and the word reading task, where both writing and visual training outperformed typing training. Neither of these tasks involve any written production, and the participants were never trained or received any feedback on their ability to orally produce the letter names or sounds.

(4) Distinctiveness processing account—According to the theory of distinctiveness processing, memories of actions carried out during study provide a heuristic by which recognition and recall performance is improved (see Chapter 1, section IV s 28-29). This is predicted to be true so long as the study actions were distinctive, meaning distinguishable from one another and non-arbitrarily related to the study items. Writing requires distinct motoric patterns for each letter, whereas the actions required to produce responses in the typing and visual study tasks were repetitive and arbitrarily related to the letter-shapes. This means that distinctiveness processing may well capture the relevant difference been writing training and non-motor training conditions.

The mechanism proposed to underlie distinctiveness processing relates to output monitoring; specifically, the claim is that during tests of recall and recognition fewer false memories arise, *and* the decision-making process is facilitated by the memory of having produced the items (or not, as it were). The faster letter recognition among writing-trained participants, including on the novel font task, is consistent with more efficient output monitoring. Specifically, if the (auditory) cue in the letter recognition task called to mind fewer possible responses for participants in the Writing Condition, then subsequent selection of the correct response would be expected to be faster. As such, the distinctiveness processing account can explain differences in RT as readily as it can differences in accuracy.

Distinctiveness processing does predict that writing, but not typing or visual study, would provide benefits to learning letters—and this can be more simply thought of as suggesting that writing training provides an additional cue to recall. This is so because only writing results in producing a response that is non-arbitrarily related to the letter-shapes. The keyboard layout is arbitrarily related, and of course visual study tasks require even less distinctive motor responses. A learning condition where participants were instructed to produce the letter names *would* be expected to facilitate learning the names, but *not* the shapes. In fact, one study of the production effect (which is most commonly explained with a distinctiveness processing account; see Chapter 1) examined how learning face-name associations was affected by producing the names, which were visually presented, by oral production (Hourihan & Smith, 2016). It was reported that while memory of the names was improved by the production effect, memory of the faces themselves was not, and thus learning the *associations* between the faces and the names was not facilitated. The authors explained this as being due to only the names having been produced, and not the faces (which would require considerable artistic drawing ability on the part of the study participants). This suggests that writing the letters while learning them facilitates letter recognition because it improves recall of the letter-*shapes*—and moreover, it does so only to the extent that the motor strokes used to write letters helps distinguish them from one another. This also suggests that learning to associate the letter-shapes with the letter names would *not* be facilitated without oral production of the names. Therefore, the prediction of distinctiveness processing is that writing experience supports letter processing tasks specifically by improving recall of the letter-shapes, but does nothing to aid learning the letter names or sounds.

(5) Grounded versus abstract cognition—The prevailing account for why results such as those reported here, showing better letter learning with writing training compared to typing and visual training, is that writing alone develops motoric representations, which are necessarily recruited during letter processing, regardless of the specific task. It is the case that the Writing Condition resulted in numerically superior performance on all of the tasks, including tasks that do not require motoric representations (e.g., letter naming), but the key question concerns the type of representations that underlie this improved performance. This information is also critical for abstractionist theory, as it predicts the existence of amodal letter representations. The focus of Chapter 4 is thus on the content of the letter representations that were learned by the participants over the course of their training. Before proceeding to that, the results of the measures of learning retention are presented in the third and final section of this chapter.

III. Learning Retention

Three measures of how well learning was retained were conducted at the follow-up time point, approximately one month after the post-training time point. In all of these analyses, the actual number of days since training had elapsed were taken into account, particularly important given that there was a wide range (13-43 days) across participants, although the average amount of time per learning condition was very similar. The results of each of these three measures is presented and followed by a final discussion of the entire chapter.

1. Letter Recognition

The descriptive statistics for Letter Recognition task administered at the follow-up time point, which was identical to that administered at post-training, are depicted in Figure 3-9 and the LMEM analysis in Table 3-10. For both accuracy (Table 3-10, Figure 3-9 left panel) and RT (Table 3-10, Figure 3-9 right panel) there was a significant effect of the actual number of days between the post-training session and follow-up, with performance declining with time ($p = 0.02$ and $p = 0.01$, for accuracy and RT respectively). However, there were no significant effects of learning Condition.

Table 3-10. LMEM of performance on the follow-up Letter Recognition test, for accuracy (left panel) and RT (right panel). Random effects included intercept and slope for trial order, by-participants, and intercept and Condition, by-items. T = Typing, V = Visual, W = Writing. *** p < 0.001, ** p < 0.01, * p < 0.05, . p < 0.1.

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	2.8599859	0.32321	8.849	<2e-16	***
days since post-test	-0.645408	0.28205	-2.288	0.0221	*
TvV	-0.000168	0.30593	-0.001	0.9996	
(T+V)vW	-0.01198	0.18808	-0.064	0.9492	
trial order	-0.224969	0.15025	-1.497	0.1343	
	marginal R^2		conditional R^2		
	0.0836613		0.48490463		

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	2720.909	24.157	112.63	<2e-16	***
days since post-test	71.186	27.702	2.57	0.0102	*
TvV	-101.255	69.122	-1.46	0.143	
(T+V)vW	-22.085	21.349	-1.03	0.3009	
trial order	-126.892	23.893	-5.31	1.09E-07	***
previous trial RT	2.464	17.745	0.14	0.8896	
	R^2				
	0.4021802				

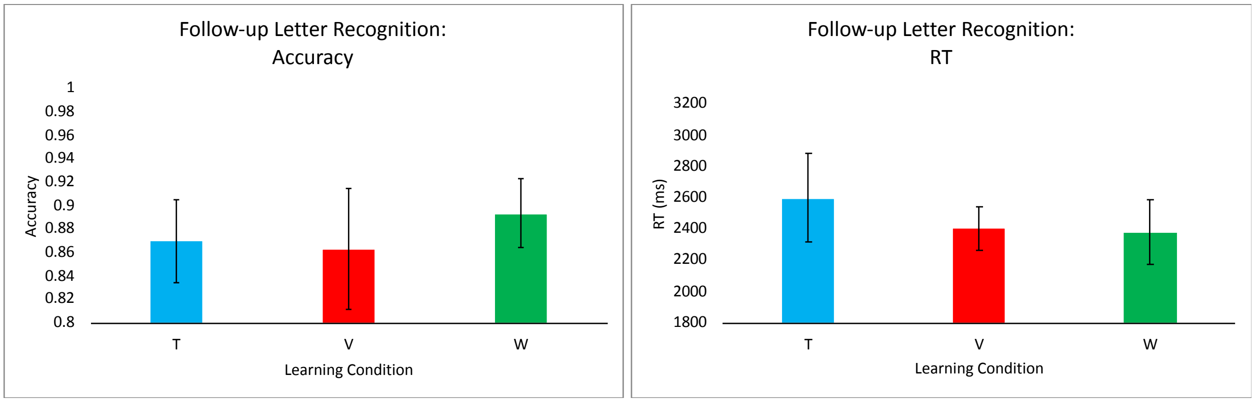

Figure 3-9. Grand mean of accuracy (left panel) and RT (right panel) for the follow-up Letter Recognition task, by Condition. Error bars reflect standard error of the mean. T = Typing, V = Visual, W = Writing.

2. Writing Letters to Dictation

The descriptive statistics for the writing-to-dictation word task are reported above in Figure 3-5 (in the "Generalization" section, right panel) and the LMEM analysis in Table 3-5 (in the "Generalization" section, right panel). There was no significant difference between the learning Conditions.

3. Letter Naming

The descriptive statistics for the letter naming task are reported in Figure 3-10 and the LMEM analysis in Table 3-11. For accuracy (Table 3-11, Figure 4-10 left panel), the better performance of the Writing Condition (82% mean accuracy) was not significantly different from the performance of the typing or Visual Conditions (71% and 73%, respectively). However, for RT (Table 3-11, Figure 3-10 right panel), the Writing Condition was significantly faster (1575ms) than the Visual Condition (1732ms), $p < 0.001$, which was in turn faster than the Typing Condition (1867ms), $p < 0.001$.

Table 3-11. LMEM of performance on Letter Naming at the post-training time point. Random effects included intercept and slope for trial order, by-participants, and intercept and Condition, by-items. T = Typing, V = Visual, W = Writing. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, . $p < 0.1$.

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	3.042954	0.332778	9.144	<2.00E-16	***
TvV	-0.22977	0.310516	-0.74	0.4593	
(T+V)vW	0.419652	0.204529	2.052	0.0402	*
trial order	-0.00241	0.068357	-0.035	0.9719	
	marginal R^2		conditional R^2		
	0.053043		0.54896515		

Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
(Intercept)	1636.134	104.699	15.627	<2.00E-16	***
TvV	-68.773	48.172	-1.428	0.1534	
(T+V)vW	-30.146	41.784	-0.721	0.4706	
trial order	-8.565	13.334	-0.642	0.5206	
previous trial RT	28.131	12.78	2.201	0.0277	*
	R^2				
	0.3748489				

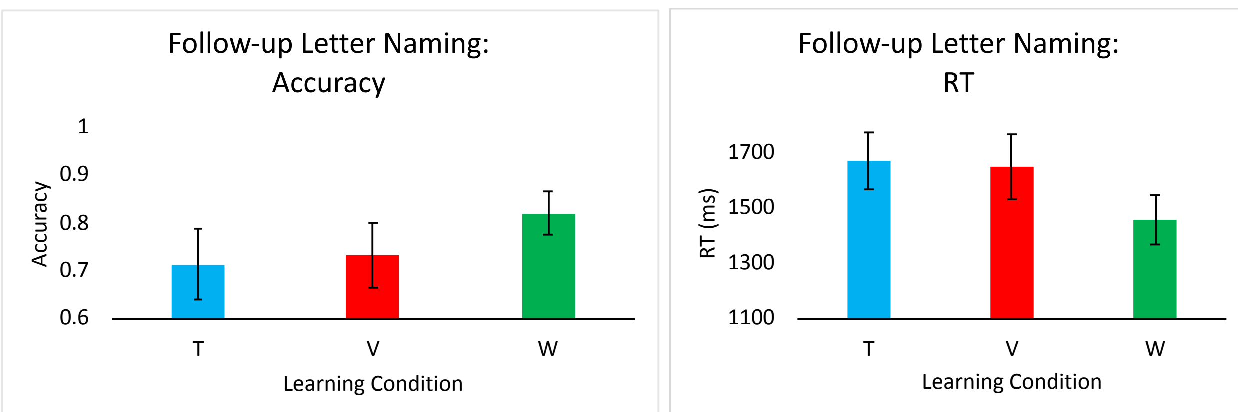

Figure 3-10. Grand mean of accuracy (left panel) and RT (right panel) for Letter Naming at the follow-up time point, by Condition. Error bars reflect standard error of the mean. T = Typing, V = Visual, W = Writing.

Discussion: Learning Retention

Performance clearly declined across all three learning conditions, with some evidence of better retention among the Writing Condition participants. There were no differences across learning conditions on letter recognition of the familiar font, but this contrasts with performance on the novel font (which was also administered at the follow-up time point; see section II "Generalization of Learning"). The only significant difference on the measures of retention was on letter naming, where Writing Condition was the fastest, following by the visual and then the Typing Conditions.

In terms of writing letters to dictation, the Writing Condition no longer significantly outperformed the others at the one-month follow-up. In fact, the Writing Condition was the only group to show a significant *increase* in the proportion of mirror-reversed errors from the post-training time point to the follow-up, from 1.7% of trials to 5.9% ($p < 0.01$ by LMEM analysis), versus an increase from 5.5% to 8.0% in the Typing Condition and a decrease from 10.5% to 8.8% in the Visual Condition (p's > 0.1). Taken together with the results from the post-training time point, the implication is that the Writing Condition is particularly helpful for learning the correct orientation of the letters, but that this ability is not especially retained, such that after a month the participants are making similar numbers of mirror-reversed errors. This is perhaps not surprising, given that mirror-reversal errors are a well-known phenomenon among children that requires extensive practice to overcome (Treiman, 2011), and the types of errors produced here by the adult participants when writing the letters was qualitatively identical to those observed in children (see Figure 3-11). What is most interesting about this may be that indeed, despite having learned to distinguish mirror-reversed pairs in the Roman alphabet (b/d, p/q), this ability clearly does not automatically transfer onto novel shapes. It should also be noted that strictly speaking, Arabic does not contain any mirror-reversed pairs, although in some fonts, there is one pair of letter-shapes that are fairly similar (initial “meem” ـمـ and final “ha” ـه). Many of the mirror-reversed letters that the participants produced were thus non-letters in Arabic.

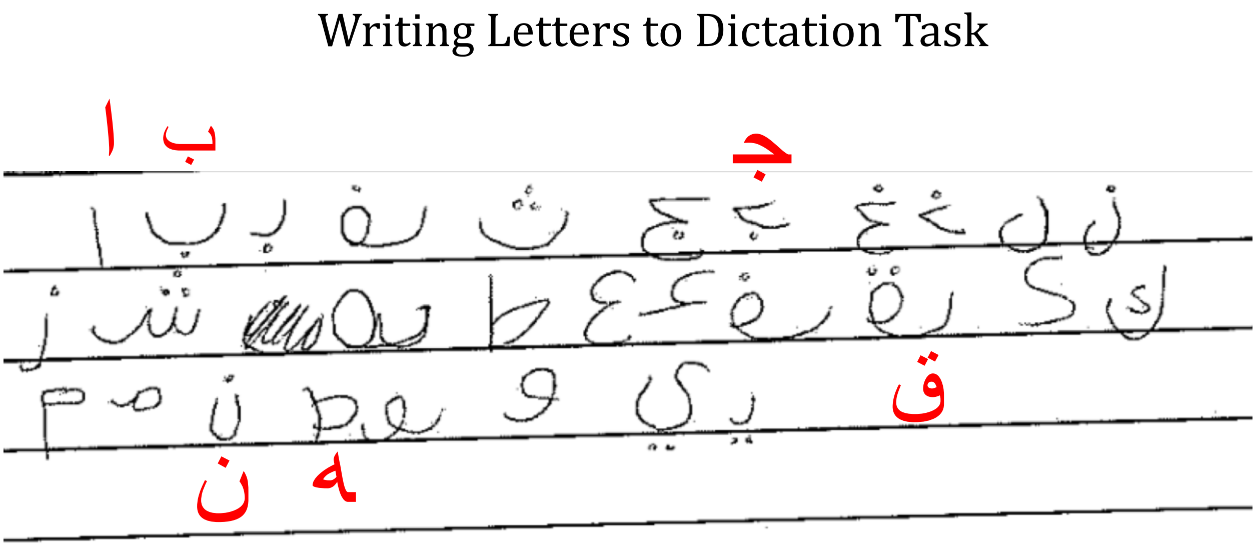

Figure 3-11. An example of mirror-reversed letters (with correct letter-shapes portayed in red) for participant EKH (Visual Condition). The letters alef, ba, and nuun (ا ب ن), left-hand side, were written correctly, while ha, jim, and qaf were mirror-reversed (جـ ـه ق), right-hand side.

As for letter naming, the Writing Condition was significantly faster to name the letters than either other condition, with the Visual Condition faster than the Typing Condition as well. It is striking that letter naming, a task which is no more similar to one training task compared to another (e.g., it is not more related to typing training than to visual training), resulted in some of the clearest advantages for the Writing Condition, both in terms of generalization at the post-training time point and retention at the follow-up. In fact, an advantage in naming for writing experience over visual experience was recently found by Bhide (2018). In that study, adult participants learned Hindi akshara (graphs) either through a writing or a visual learning condition. The author noted that the better performance on akshara naming for those with writing experience was unexpected, but it was found to be significant for both RT and accuracy, and across two days of testing. No specific hypothesis was given for this result, other than a general appeal to the theory of desirable difficulty.

VI. General Discussion of Letter Learning Results

The primary question addressed here is: Are the effects of writing experience due to motor learning *per se*, or to other variables confounded with the writing experience? Taken together, the findings suggest (1) that there are indeed benefits of writing experience, the extent of which is broader than previously known, and (2) that numerous alternative accounts previously put forth can largely be dismissed. However, as will be discussed, a few questions remain, some of which are addressed in Chapter 4, and others which are considered at the end of this chapter as possible future directions.

The Effects of Training Conditions on Learning Letters

The Writing Condition was indeed the most consistently effective learning condition across the broad set of measures of learning investigated here: the trajectory of learning, generalization to new tasks, and retention. Strikingly, on every single measure, the Writing Condition was either significantly or numerically the best performing, with the exception only of the rate of improvement on accuracy and RT on the letter recognition test (on which the typing experience improved most quickly). This is even more impressive considering that participants in this condition tended to reach those levels of performance in *less* time

(3.7 sessions of training on average, versus 3.9 for typing and 4.3 for vision). Although the Typing Condition led to very rapid improvement on letter recognition, it generally showed poorer generalization, and had the worst retention. Moreover, the Typing Condition's fast rate of improvement was associated with a comparatively worse performance on the initial session (both lower accuracy and slower RT). Interestingly, while the Visual Condition resulted in slower progress on letter recognition, it generally outperformed the Typing Condition. In terms of the broad issues under discussion, the results are unequivocal in supporting that there are benefits of writing practice for letter learning, and convey clearly that the nature of these benefits extends from the rate of learning to generalization to retention.

These findings in themselves have important educational implications, and support the conclusion made by others (see Chapter 1) that writing experience does provide benefits for letter learning. The weight of the evidence suggests that there is something unique about writing, given that the typing and visual training conditions led to such different behavior across the different tasks. And the variable input account seems an insufficient explanation, given that all participants were presented with four fonts to learn from (just as in Li & James, 2016).

One possibility why writing training may be so beneficial for learning letters is it requires learning to decompose the letter-shapes into components, which are needed to form the basis motoric strokes, but also serve to enhance a visuo-spatial, geometric representation of the letter. Such decomposition of a (relatively) complex shape into component features is not required for typing or visual learning conditions. The study of

Bhide (2018) is however *not* consistent with this account, as the visual training conditions there involved either constructing complex akshara from components, or deconstructing complex akshara into components. In that study, both of these visual training conditions resulted in poorer performance than writing training. However, the akshara components were themselves more complicated than single visual features or strokes (i.e., they remained composed of multiple parts), which leaves open the possibility that a different type of visual training could improve letter learning.

The next chapter reports on the results of analyses that reveal the content of the learned letter representations, as reflected both in behavior (via the Same/Different Judgement task) and in neural activity (via representational similarity analysis of fMRI data). Those analyses most directly test the grounded cognition position that sensory/motor activation during letter perception reflects sensory/motor, *and not any amodal,* letter representations. As outlined in Chapter 2 ("RSA: Behavioral Performance Analyses", s 94-95), the behavioral results that were presented here are crucial for further testing this theory, as it also predicts that motoric representations learned by writing training are implicated in behavior, and as such there should be an association between the motoric representations and performance on letter processing tasks.

Chapter 4 – Results: Letter Representations

This chapter presents the results of analyses targeted at uncovering the content of letter representations, and how those representations were affected by the different training conditions under which the letters were learned. These results address the second and third primary questions: (2) Does writing experience recruit only sensory/motor representations? And (3) which types of representations, motoric or otherwise, underlie the behavioral benefits of writing experience? In Chapter 3, the behavioral results of the longitudinal training study, in which participants learned Arabic letters through either typing, visual, or writing training tasks, affirmed what has been reported elsewhere in the literature: writing experience leads to superior performance on a range of letter processing tasks, relative to non-motor learning experiences. Such evidence has been taken by many as supporting grounded cognition theories, claiming that the reason writing is beneficial for learning letters is that letter processing depends on sensory and motoric representations. This claim has been further supported by findings of a "sensory-motor" brain network that activates during even passive letter viewing. However, no evidence has been put forth demonstrating that this neural activity corresponds entirely to sensory and/or motor letter representations. It cannot be taken for granted that the "visual-motor letter processing" network (James, 2017) instantiates only sensory/motor representations, given that it includes cortex outside of the primary sensory and motor areas. One alternative type of letter information that could be represented within this network is symbolic letter identity (SLI), an amodal representation that is proposed by abstractionist theory. According to an abstractionist account, an amodal SLI representation allows, for example, different allographs of the same letter to be conceived of as identical, despite differences in their concrete instantiations.

The first three sections of this chapter present results that directly address this issue, by providing information about the content of the letter representations that were learned by those who had writing training, and how those representations differ from those who had non-motor training. In the first section (I. "Letter Representations in Behavior"), analyses of the same/different letter judgment task reveal how the multiple letter representations (visual, motoric, phonological, and abstract) influenced letter perception, and in particular how this changed from pre- to post-training, and for each of the three training conditions. In the second section (II. "Letter Learning in the Brain"), the brain regions that showed changes in activity from pre- to post-training selectively in response to viewing Arabic letters were identified in order to in order to provide the basis for the representational similarity analyses (RSA) that were used to reveal the types of letter representations instantiated in these areas as a result of learning. Accordingly, the third section (III. "Letter Representations in the Brain") presents the results of applying the RSA technique, and reports on five types of letter representations, where they are instantiated in the brain, and whether they differ as a consequence of the different training conditions.

The set of results reported in the third section answer in particular the third main question of the dissertation (which types of representations underlie the behavioral benefits). As described in Chapter 3, four measures of individual differences in letter processing tasks (letter recognition, letter naming, writing letters to dictation, and reading words) are used here to evaluate interactions between behavioral performance and each of the five types of letter representations examined. This information is used to further examine the prediction of grounded cognition, specifically that *superior behavioral performance* on letter processing tasks is associated with sensory/motor representations, and as such helps understand the role of the various letter representations in letter processing. While each section concludes with an interim discussion, a final section (IV. "General Discussion of Letter Representations") is used to revisit the three main questions of the dissertation in light of the results reported in this chapter.

I. Letter Representations in Behavior

This section presents the results of the same/different letter judgment task, which was administered twice: at pre-training and post-training. The same/different task has been used extensively in the past to uncover the types of letter representations that influence letter perception. The logic that supports these types of inferences is that slower RTs to decide that two physically-different shapes are in fact different indicates that the underlying representations of those two shapes are more similar than those of shapes that are responded to more quickly. By using simultaneous multiple regression (specifically, LMEM), differences in RT across pairs of letters are explained as the result of a decision-making process (i.e., deciding the pair of shapes is "different") that takes into account all of the sources of information such that responses will be slowed not only if the two letters are more visually similar, but also if they have more similar representations along other dimensions. Observers may be influenced by such information despite it being task-irrelevant (see Wiley, Wilson, & Rapp, 2016).

As a visual aid to interpreting the results of this analysis, a dendrogram representing the results of a hierarchical clustering analysis (HCA) of the data is also presented. The HCA is based on (correct) RT in response to pairs of different letters, and reflects the differences in RT across pairs by organizing the letters into a hierarchical structure that depicts their perceptual similarity. Letters that are closer together in the dendrogram are thus those that are perceptually more similar. As with the LMEM analyses, the HCA was conducted on the data from both the pre-training and post-training administrations of the Same/Different Judgement task. The results from each of those time points can be compared to one another through a "tanglegram" (Galili, 2015), which simply arranges two dendrograms in a way that highlights how the hierarchical structure of the perceptual letter space changed across the time points.

Results: Same/different Letter Judgment Task

The descriptive statistics for the Same/Different Judgement task are reported in Table 4-1. Accuracy was high overall, at both time points: 95.6% and 96.5%, respectively for same and different pairs pre-training, and 96.2% and 97.1% at post-training. The RTs were also very similar across time points and for both same and different pairs: 676ms and 660ms for same and different pairs respectively at pre-training, and 689ms and 660ms post-training.

The results of the task are visualized in Figure 4-1 as a tanglegram depicting the dendrograms of the Arabic letters, based on median RTs on correct trials at the pre-training time point (Figure 4-1, left-hand side) and at the post-training time point (Figure 4-1, right-hand side).Pairs of letters that are in the same relationship to each other at both time points are indicated by solid black/non-crossing lines of color. Letters whose relative position in the hierarchy changed from pre- to post-training are indicated by dotted black lines/crossing lines of color. One result evident in the tanglegram is that, of the six pairs of allographs included in the task (the letters “ba”, “jim”, “shin”, “qaf”, “kaf”, and “ya”), none are paired together in the closest clusterings at the pre-test time point, but two are paired together at the post-training time point (“jim” and “qaf”). Two of the other four pairs (“shin” and “kaf”) are perceptually closer at post-training relative to pre-training. The two pairs of allographs that are not closer at post-training compared to pre, the letters “ba” and “ya”, seem to be heavily influenced by the fact that one of the allographs of “ba” and one of the allographs of “ya” are extremely perceptually close. In fact, these two letter-shapes are the single most similar pair, differing only in that “ya” has one additional dot (see Figure 4-1, bottom two letters).

Table 4-1. Descriptive statistics for the same-different judgment task.

Learning Experience:	same								different							
	pre				post				pre				post			
	acc		rt		acc		rt		acc		rt		acc		rt	
	mean	*sd*	mean	*sd*	mean	*sd*	mean	*sd*	mean	*sd*	mean	*sd*	mean	*sd*	mean	*sd*
Typing	95.8%	*3.6%*	712	*125*	95.7%	*3.4%*	696	*115*	97.1%	*1.5%*	692	*102*	97.0%	*2.2%*	678	*117*
Vision	95.6%	*2.1%*	629	*50*	96.2%	*2.0%*	626	*66*	97.0%	*1.7%*	630	*73*	96.7%	*1.7%*	600	*57*
Writing	95.4%	*8.5%*	687	*106*	96.7%	*3.4%*	741	*126*	95.3%	*5.2%*	659	*92*	97.7%	*1.0%*	703	*101*

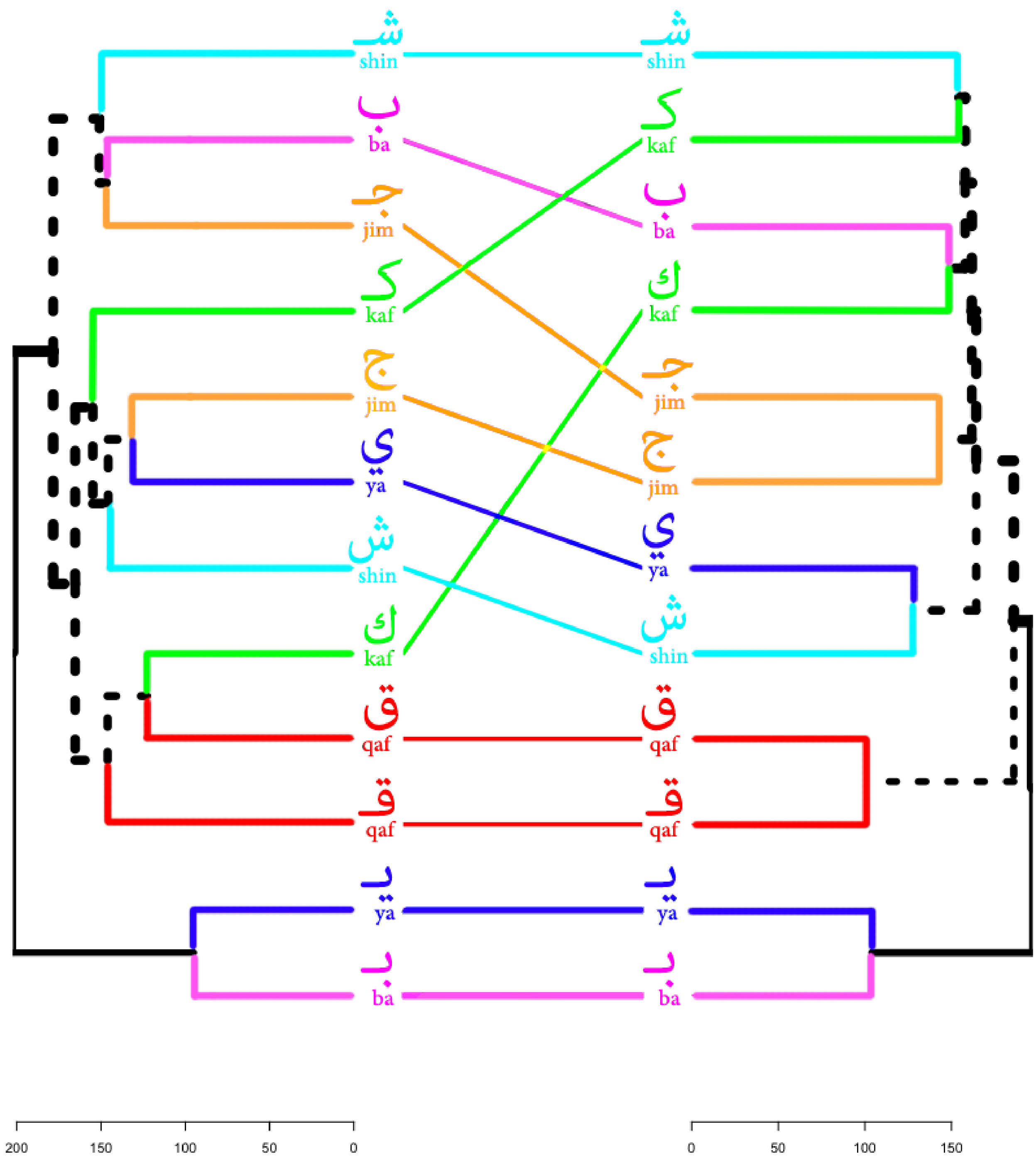

Figure 4-1. Tanglegram comparing the hierarchical clustering of 12 letter-shapes at pre-training (left-hand side) to post-training (righthand side). The letter names appear below the shapes. Allographs are coded with the same color to emphasize their relationship.

The LMEM analyses assess the contribution of five types of letter representations to determining the RT of the different pairs: pixel overlap (low-level visual representation), visual features (higher-level visual representation), motor bistrokes (motoric representation), letter names (phonological representation), and symbolic letter identities (amodal representation). Full details on the LMEM analyses, including the computation of the five measures of letter representations, are available in Chapter 2 (section III. "Behavioral Analyses"). Because the predictors for each of the five types of representation were entered in simultaneous multiple regression, significant effects reflect *unique* contributions to explaining the variance in RT[12]. These results are presented for the pre-training time point in Table 4-2, and the post-training time point in Table 4-3.

Table 4-2. Results of the LMEM analysis of RT on correct "different" trials of the Same/Different Judgement task, at the pre-training time point. T = Typing, V = Visual, W = Writing. SLI = symbolic letter identity.

	Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
	(Intercept)	671.8920	68.2030	9.8510	< 0.0001	***
	Previous Trial RT	39.9450	9.3050	4.2930	< 0.0001	***
	Trial Number	-11.5370	3.4130	-3.3810	< 0.0001	***
Learning Experience Main Effects	TvV	-34.1226	6.5547	-5.2060	< 0.0001	***
	TvW	17.0260	28.8460	0.5900	0.5550	
	VvW	-51.2240	10.6530	-4.8080	< 0.0001	***
Letter Representations: Main Effects	Pixel Overlap	8.5360	2.3200	3.6790	0.0002	***
	Visual Features	2.4490	2.7320	0.8960	0.3702	
	Motor Bistrokes	4.4620	2.5500	1.7500	0.0801	.
	Letter Names	-4.0510	3.2150	-1.2600	0.2076	
	SLI	-5.8990	6.8590	-0.8600	0.3897	
Learning Experiences X Letter Representation Interactions	TvV:Pixel Overlap	-4.0629	2.6121	-1.5550	0.1198	
	TvW:Pixel Overlap	1.6940	7.3490	0.2300	0.8177	
	VvW:Pixel Overlap	-6.4320	5.6610	-1.1360	0.2558	
	TvV:Visual Features	-1.6594	3.2314	-0.5140	0.6076	
	TvW:Visual Features	-1.2000	23.2440	-0.0520	0.9588	
	VvW:Visual Features	-4.5190	13.2870	-0.3400	0.7338	
	TvV:Motor Bistrokes	-0.3067	2.9154	-0.1050	0.9162	
	TvW:Motor Bistrokes	4.5090	10.8630	0.4150	0.6781	
	VvW:Motor Bistrokes	3.8960	7.3330	0.5310	0.5952	
	TvV:Letter Names	3.4549	3.0707	1.1250	0.2605	
	TvW:Letter Names	-11.7480	6.2710	-1.8734	0.0640	.
	VvW:Letter Names	-4.8380	6.5600	-0.7370	0.4608	
	TvV:SLI	-4.1128	4.9332	-0.8340	0.4045	
	TvW:SLI	-4.6350	9.3020	-0.4980	0.6183	
	VvW:SLI	-12.8610	14.4390	-0.8910	0.3731	

[12] All Variance Inflation Factors were < 5.

Table 4-3. Results of the LMEM analysis of RT on correct "different" trials of the Same/Different Judgement task, at the post-training time point. T = Typing, V = Visual, W = Writing. SLI = symbolic letter identity.

	Fixed effects:	Estimate	Std. Error	z-value	Pr(>|z|)	
	(Intercept)	674.0509	5.6466	119.3740	< 0.001	***
	Previous Trial RT	40.1005	3.7074	10.8160	< 0.001	***
	Trial Number	2.2645	4.5904	0.4930	0.6218	
Learning Experience Main Effects	TvV	-23.9523	5.8215	-4.1140	< 0.001	***
	TvW	-39.5752	10.8847	-3.6360	0.0003	***
	VvW	-87.4894	6.2823	-13.9260	< 0.001	***
Letter Representations: Main Effects	Pixel Overlap	6.5743	2.2536	2.9170	0.0035	**
	Visual Features	2.6555	2.6295	1.0100	0.3125	
	Motor Bistrokes	10.4002	2.3622	4.4030	< 0.001	***
	Letter Names	-4.9171	2.5005	-1.9660	0.0492	*
	SLI	21.9007	4.1115	5.3270	< 0.001	***
Learning Experiences X Letter Representation Interactions	TvV:Pixel Overlap	3.5843	2.4881	1.4410	0.1497	
	TvW:Pixel Overlap	-5.1284	4.2641	-1.2030	0.2291	
	VvW:Pixel Overlap	2.0401	4.2575	0.4790	0.6318	
	TvV:Visual Features	-1.7502	2.9811	-0.5870	0.5571	
	TvW:Visual Features	8.0720	4.5978	1.7560	0.0792	.
	VvW:Visual Features	4.5716	4.4691	1.0230	0.3063	
	TvV:Motor Bistrokes	-3.8782	2.5661	-1.5110	0.1307	
	TvW:Motor Bistrokes	-4.5766	4.1209	-1.1110	0.2668	
	VvW:Motor Bistrokes	-12.3328	4.1398	-2.9790	0.0029	**
	TvV:Letter Names	-6.6837	3.2414	-2.0620	0.0392	*
	TvW:Letter Names	12.7220	4.8838	2.6050	0.0092	**
	VvW:Letter Names	-0.6451	4.5550	-0.1420	0.8874	
	TvV:SLI	18.4625	5.8560	3.1530	0.0016	**
	TvW:SLI	-52.9740	6.9412	-7.6320	< 0.001	***
	VvW:SLI	-16.0498	7.6182	-2.1070	0.0351	*

For the pre-training time point (Table 4-2), there were no significant interactions with training group. The only letter representation predictor that was significant was that of pixel overlap, beta estimate = 8.5. In the interest of interpretation, this equates to a predicted increase of 36ms for a pair of letters with 75% pixel overlap compared to 25% (the actual stimuli ranged from 4% to 83% pixel overlap). Overall, the LMEM explained 10.3% of the variance in RT by fixed-effects alone, 28.7% in total including fixed- and random-effects.

For the post-training time point (Table 4-3), a number of significant differences emerged. In terms of the main effects of letter representations: there was a significant effect of pixel overlap, beta estimate = 6.6, translating to a 27ms increase in RT for a pair of letters sharing 75% versus 25% of their pixels. There was also a significant effect of motor bistrokes, beta estimate = 10.4, translating to a 19ms increase in RT for a pair of letters sharing 75% of their motor features versus 25%. There was a significant effect of letter names, beta estimate = -4.9 (12ms *decrease* in RT for a pair of letters sharing 75% versus 25% of their phonological features). Finally, there was a significant effect of SLI, beta estimate = 21.9, translating to an 22ms increase in RT for pairs of letters sharing the same identity (i.e., allographs). Overall, the model explained 13.2% of the variance in RT by the fixed-effects alone, and 34% in total from both the fixed- and random-effects.

All of these main effects, with the exception of pixel overlap, were modulated by interactions with the learning conditions. Separate LMEM were conducted to assess the significance of the effects for each learning Condition, when there were such interactions. For the motor bistrokes, there was a significant interaction showing that the effect was significantly larger for the Writing Condition compared to the Visual Condition with an effect size of 30ms, $p < 0.001$ (compared to the main effect reported of 19ms), whereas the Visual Condition resulted in a non-significant effect size of 7ms, $p = 0.16$. The Typing Condition showed a significant but smaller effect size of 21ms ($p < 0.05$).

For letter names, the interactions revealed that participants in the Typing Condition differed significantly from participants in both the visual and Writing Conditions. In fact, the Visual and Writing Conditions had effect sizes of similar magnitude, -24ms and -22ms (compared to the main effect size of -12ms), although the effect was only significant for the Visual Condition ($p = 0.01$ versus $p = 0.35$). However, the Typing Condition resulted in a trend toward an effect in the opposite direction of 9ms, $p = 0.12$.

Finally, the interactions with SLI revealed that each learning Condition differed from the others. The effect sizes for each learning Condition were -16ms ($p = 0.09$), 58ms ($p < 0.001$), and 90ms ($p < 0.001$) for the Typing, Visual, and Writing Conditions, respectively. Thus, participants in the Writing Condition showed the greatest effect of SLI, whereas the

Typing Condition resulted in a trend in the opposite direction (with slightly faster RT to pairs of allographs compared to pairs of non-allographs).

Discussion

Similar to the findings reported here from the pre-training timepoint, previous research on letter perception by naïve participants performing the same-different task with the Arabic alphabet (Wiley et al., 2016) also only found evidence of visual representations. In contrast, evidence of not only visual but also of motoric, letter name, and SLI representations was found for expert observers, both of the Arabic alphabet (Wiley et al., 2016) and the Roman alphabet (Rothlein & Rapp, 2017). These findings are paralleled here in the post-training assessments. The novel insights provided by these results stem from the manipulation of the training conditions under which the participants learned the letters, and thus they provide a deeper understanding of how letter representations are affected by learning experience. On this basis, the results have implications for the grounded cognition/abstractionist debate in particular, and more generally for understanding the effects of writing experience on letter learning. There are two results in particular that merit further discussion.

First, motoric representations were found as a main effect, but not uniquely following writing training. There was evidence that motoric representations had a significantly stronger influence on participants who had writing training compared to those who had only visual training, but there was no significant difference between the writing and the typing training. There are two possible explanations for why this motoric representation may have influenced letter perception even in the absence of writing training. The first is that the same-different task was administered last during the post-training session, shortly after all participants had been asked to write both letters and words to dictation. The mere fact that participants were able to complete that task even if they had never written the letters before (albeit with less accuracy than those who had) clearly indicates that they had sufficient knowledge to write the letters from memory. This indicates that it is not the case that writing requires stored motor plans from previous writing experience. The motor plans used by these participants were presumably constructed in an online fashion, and the representations used for such motor planning may differ from those stored in long-term memory by those with more extensive writing experience. One possibility for how this was done was to make use of the visual dynamic information that was presented in the training videos—that is, the letters were written based on *visual* memories of the letter animations. Either way, writing the letters in the same session as the same-different task could plausibly have influenced the letter perception task, albeit more weakly than for participants in the Writing Condition who did have stored motor plans.

A second possibility is that the similarity of the pairs of letters in terms of motor features is at least partially confounded with the similarity of the training videos. Letters with similar strokes necessarily had similar videos, in terms of the spatial-temporal dynamics of the pixels as they were revealed on the screen. The importance of the training videos for forming the participants' letter knowledge should not be underestimated, as they were exposed to many repetitions of these videos, and (a) they had to pay some attention to these videos in order to complete their training tasks, and (b) these videos were the only time during which they were exposed to the letter names and sounds. In fact, the letter names and sounds were presented simultaneously with the dynamic frames of the videos, thus necessarily there would be a high association between the dynamic motion in the videos and the letter names and sounds. Therefore, there is a possibility that what the participants had in common, as captured by the significant main effect of the motor feature overlap on RT in the same-different task, was activation of the memory traces of the training videos, including the dynamic visual features. Dynamic visual information is known to effect perception of static images, including letters (e.g. Babcock & Freyd, 1988; see Chapter 1). One way to potentially de-confound the two possibilities (i.e., motor features versus dynamic visual features) is to consider neuroimaging data. Given the expectation that the Writing Condition would lead to a different type of motoric representation than the other two, the RSA technique allows for finding differences across the training conditions that cannot be found in analysis of the Same/Different Judgement. For example, the location of any motoric letter representations could differ between writing-trained and non-motor-trained participants (whereas, of course, no such distinction is possible in a RT analysis). This possibility is examined in section III of this chapter.

Second, an amodal letter representation, SLI, was found to influence both the writing-trained and visually-trained participants. This evidence in itself presents a challenge to any grounded cognition views that refutes the existence of amodal representations—they are challenged to explain how the SLI representation is not truly amodal. Moreover, this representation was found to be significantly stronger among participants in the Writing Condition, which is even more problematic for grounded theories—those who had the most “grounded” experience with the letters were those who developed the strongest *amodal* representation. The abstractionist proposal is that SLI representations serve to mediate between the different letter representations (see Chapter 1, Figure 1-1); if this is so, then finding stronger SLI representations among those with writing experience is consistent with the general advantages of writing training for letter learning. In fact, it is striking that the overall pattern of behavioral results, with writing training clearly leading to the best performance on letter processing tasks and typing training the worst, parallels the results of the Same/Different Judgement task: not only did writing-trained participants show the strongest influence of SLI, the only group that did not show any significant effect of SLI was the Typing Condition.

With regard to SLI, the Typing Condition participants showed a marginal trend in an unexpected direction, with faster responses to pairs of allographs. At the same time, they also showed a trend toward slower responses to letters with similar names. One concern is that the reverse signs on the effect of letter names and SLI, which was found for each group, could be a statistical artifact known as a “suppression effect” (an aspect of Lord's paradox, see Arah, 2008) due to the positive correlation between the letter name predictor and the SLI predictor (driven by the fact that allographs have identical letter names). This possibility was ruled out by analyzing the data from the non-allograph pairs only, including only the letter name predictor and dropping the other four types of letter information predictors. In that analysis, the pattern of results was the same, with the Visual and Writing Conditions still showing negative relationship between RT and letter name similarity, and the Typing Condition showing a positive relationship—thus, the results were not driven by the correlation between the SLI and letter name predictors..

II. Letter Learning in the Brain

The analysis of the Letter Learning Network fMRI task (see Chapter 2, sections II and IV), administered at both the pre-training and post-training scanning sessions, was used to determine regions-of-interest (ROIs) in which to conduct a representational similarity analysis (RSA). Specifically, the results presented here reveal which brain regions showed changes in activity, from pre- to post-training, selectively in response to viewing Arabic letters. Previous similar analyses of fMRI data, comparing the strength and location of neural activation across participants who have learned letters under different training conditions, have reported activation in what have been referred to as "sensory-motor" areas, among others. The mere location of this activation has been taken as evidence that cognition is grounded, but that conclusion assumes that the activity reflects the processing of sensory and/or motor representations, even though many of these areas lie outside primary somatosensory and motor cortex. In order to test that claim, it is first necessary to determine whether such sensory/motor activation was observed for the participants who underwent this longitudinal study, and to carry out RSA in these areas to investigate the nature of the representations reflected in the pattern of activity (section III. "Letter Representations in the Brain").

Letter Learning Network (LLN)

The results of the univariate analysis of the orthographic localizer task (see Chapter 2, section II. "Neuroimaging Methods", 81) are reported in Table 4-4 and Figures 4-2 and 4-3. In total, 25 anatomical regions were identified as showing a greater increase in pre to post training activity in response to Arabic letters, relative to Roman letters: 9 bilateral regions, 5 regions in the left hemisphere, and 2 regions in the right hemisphere (Table 4-4). These regions are largely bilateral, with the exception of the STG and cuneus, which were only involved in the left hemisphere. These 25 regions were named on the basis of their anatomical locations). Each of these regions showed a positive t-value, i.e., relatively greater increase in activity in response to Arabic letters from pre to post-training than for Roman letters—no region showed a significant effect in the other direction. The total volume of the LLN was 4,535 voxels (3x3x3mm).

Table 4-4. List of anatomical regions as identified in the Letter Learning Network (LLN), voxelwise FDR correction $q < 0.05$. meSFG = medial superior frontal gyrus, DLPFC = dorsolateral prefrontal cortex, MFG = middle frontal gyrus, pre-SMA = pre-supplementary motor area, SPL = superior parietal lobule, FEF = frontal eye fields, IFG = inferior frontal gyrus, preCG = precentral gyrus, SMG = supramarginal gyrus, STG = superior temporal gyrus, IPL = inferior parietal lobule, VLPFC = ventrolateral prefrontal cortex

bilateral	L only	R only
meSFG	FEF	IPL
cerebellum	IFG	VLPFC
DLPFC	preCG	
MFG	SMG	
cingulate	STG	
pre-SMA		
precuneus		
SPL		
calcarine		

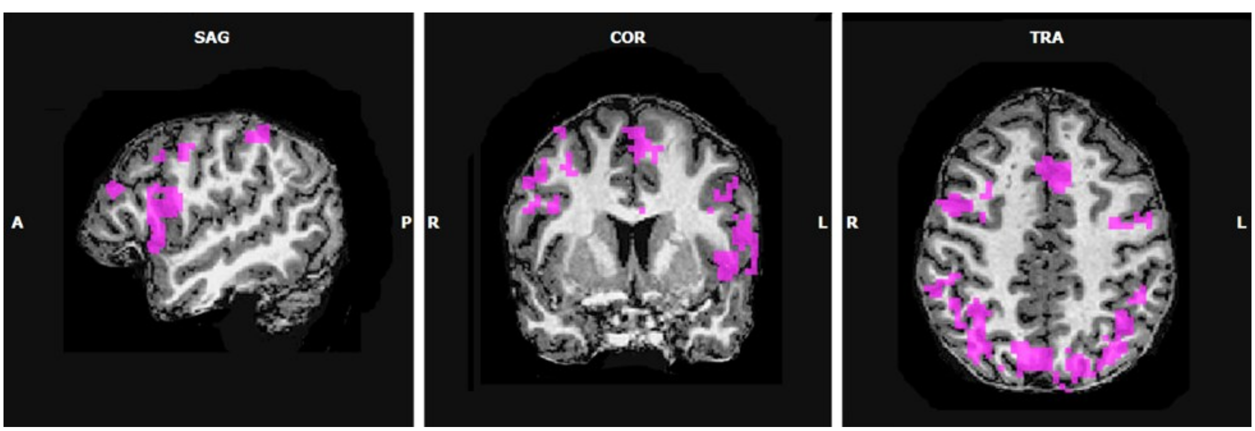

Figure 4-2. Letter Learning Network (LLN) in left frontal superior regions. A = anterior, P = posterior, R = right, L = left. SAG = sagittal, COR = coronal, TRA = transverse. MNI coordinates (-50, 7, 45).

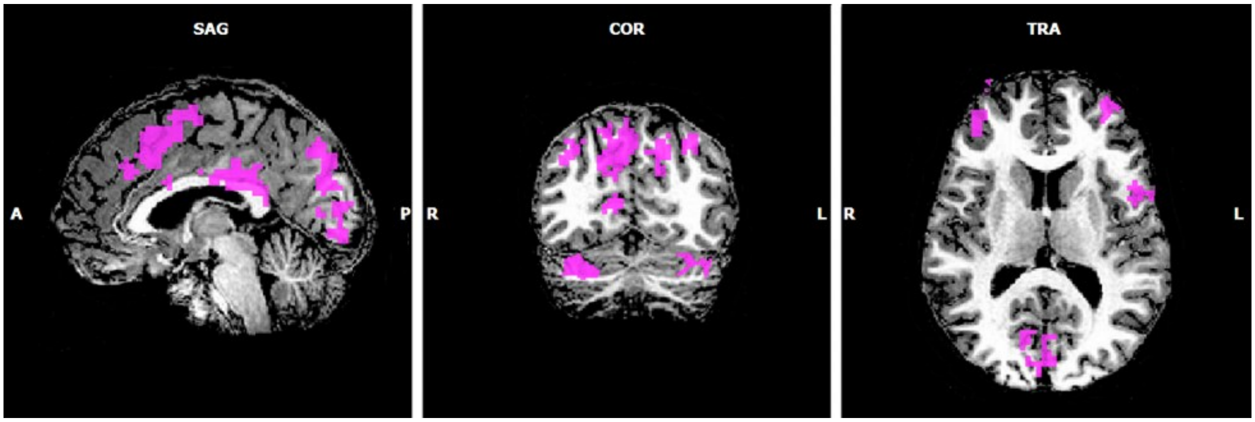

Figure 4-3. Letter Learning Network (LLN) in medial and posterior regions. A = anterior, P = posterior, R = right, L = left. SAG = sagittal, COR = coronal, TRA = transverse. MNI coordinates (-2, -70, 11).

Ventral Occipital-Temporal (vOTC) Regions

The same procedure used to define ROIs as part of the LLN was used, except with a different contrast (Arabic letters pre + post > checkerboards pre + post) in order to identify the areas within ventral temporal-occipital cortex (vOTC) that were responsive to Arabic letters generally, and not specifically areas that gave (univariate) evidence of changes as a result of learning. Only areas showing *greater* activity to Arabic letters compared to checkerboards were included; moreover, this contrast was restricted by an anatomical vOTC mask (extending from Y = -80 to -25, and Z = -34 to -5, bilaterally). The resulting vOTC ROIs are depicted in Figure 4-4, and included the fusiform gyri, the lateral occipital sulci, and parts of extrastriate cortex including the region of V5/MT (middle temporal visual area). The bilateral vOTC ROIs contained in total 1,766 voxels (3x3x3mm), extending across x = (-53, -

31), y = (-88 -46), and Z = (-26, 10) in the left hemisphere and from x = (27, 56), y = (-90, -43), and Z = (-29, 9) in the right hemisphere.

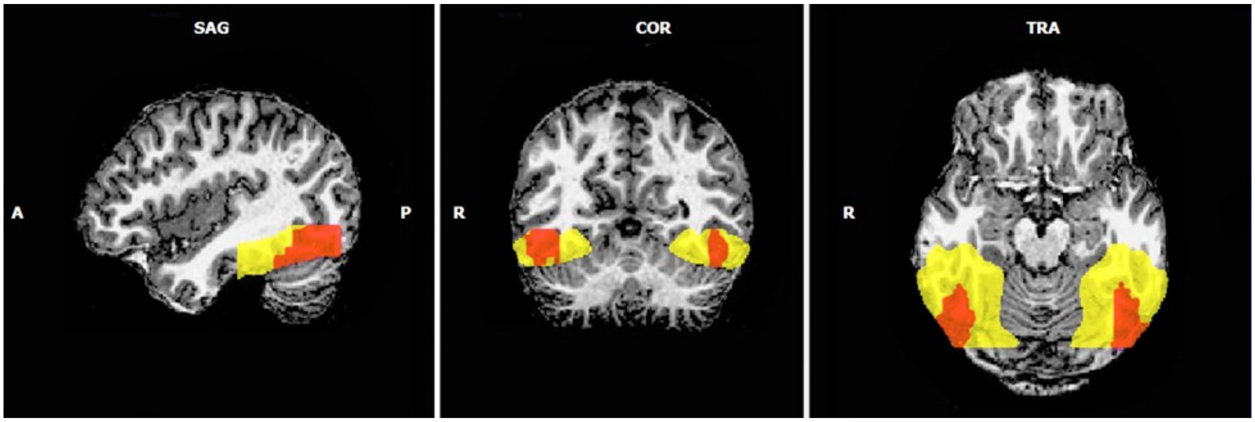

Figure 4-4. Ventral occipital-temporal (vOTC) regions responsive to Arabic letters more than checkerboards. Yellow = anatomical vOTC mask, red = voxels selected by contrast of Arabic letters > checkerboards. A = anterior, P = posterior, R = right, L = left. SAG = sagittal, COR = coronal, TRA = transverse. MNI coordinates (-40, -58, -17).

Summary & Discussion

Noticeably absent from the Letter Learning Network ROIs were any areas of the fusiform cortex, in either hemisphere. Presumably this was because, unlike the areas identified in the LLN, the fusiform cortex was highly responsive to the Arabic letters at the pre-training time point—therefore, in the post-versus-pre contrast, no voxels survived the FDR correction. It is furthermore unsurprising that this area would be responsive to Arabic letters even among naïve observers, given that it is known to respond to orthographic-type shapes more than other visual stimuli, even if those shapes are unfamiliar (e.g., Hebrew letters > line drawings, among non-Hebrew readers, Baker et al., 2007). For that reason, a less restrictive contrast was used to localize regions with vOTC that were simply responsive to Arabic letters relative to checkerboards, The resulting ROIs in vOTC are consistent with areas commonly reported as belonging to the visual word form area, or VWFA (Dehaene et al., 2002; Dehaene, Cohen, Morais, & Kolinsky, 2015; McCandliss et al., 2003; Vogel, Petersen, & Schlaggar, 2014), and extend bilaterally the length of the fusiform gyrus, as well as extrastriate and visual association areas of the occipital lobes.

The union of the set of ROIs from the LLN together with the bilateral vOTC regions were used to define the space of the subsequent searchlight RSA analyses. This combined area included the ROIs that have been previously identified as part of the "visual-motor letter processing system" (James, 2017; see Fig. 1, 2): the fusiform gyrus, the superior temporal/supramarginal gyrus, the precentral gyrus, the middle frontal gyrus, and the inferior frontal gyrus. The term "visual-motor", however, may be a misnomer, in that it remains to be shown the extent to which the activity across this network in fact reflects visual and/or motoric letter representations. In the interest of better understanding the role of these areas in letter processing, the following section presents the results of RSA, which was used to assess the nature of the neural representations throughout the combined LLN-vOTC network,.

III. Letter Representations in the Brain

This section presents the findings that most directly answer the second primary question of this dissertation: does writing experience result only in letter representations that are sensory/motor in nature? While the results of the behavioral same/different task revealed that motoric letter representations were not unique to individuals who had writing experience, the possibility was raised that this could be due to a confound between the motoric and dynamic visual representations of the letters. While this possibility could not be addressed through the Same/Different Judgement task, it is possible for the neural analyses to do so because, unlike for RT analyses, information about both the neural location and strength of motoric letter representations may differ across training conditions.

It should be pointed out that the direction of the relationships uncovered by RSA, between the letter similarity measures on the one hand (e.g., motoric representations), and the neural similarity measure on the other hand (i.e., the Euclidean distance between the vectors representing the neural responses to stimuli; see Chapter 2, section II. "Neural Methods"), can be either positive or negative. Thus, for example, greater visual similarity between letter pairs could be associated with relatively *more similar* neural activation patterns—or, alternatively, more visually similar letters could have more *dissimilar* neural representations. Possible interpretations of each of these are discussed at the end of this chapter.

This section is organized as follows: first, a brief report of the in-scanner behavioral performance on the symbol detection task (SDT), which provided the data for the RSA. Then, the results of the RSA of the post-training data are presented for each of the five types of letter representations in turn: (1) low-level visual (pixel overlap), (2) higher-level visual (visual features), (3) motoric (motor bistrokes), (4) phonological (letter names), and (5) amodal (SLI). Within these subsections, two types of RSA results are reported. First, in addition to information about the location of clusters instantiating each type of letter representation, LMEM was used to also determine whether there were differences in the strength of those representations across training conditions. This directly bears on the issue of what types of letter representations are associated with each of the learning Conditions.

Second, in a similar way, LMEM was used to determine whether the strength of those representations covaried with individual differences on any of four behavioral measures: letter recognition, letter naming, writing letters to dictation, and word reading.

In-scanner Behavioral Performance

Performance accuracy on the symbol detection task in the scanner was very high, for all Conditions (see Table 4-5): the false alarm rate on letter trials was virtually identical at both time points, 0.7% on average (false alarms were removed from the subsequent analyses). Two participants had one entire run removed from the analyses, for having a hit-rate more than 3 standard deviations below the grand mean (25% and 9%). The resulting average hit rates were 95% and 91%, and RT was 556ms versus 617ms, respectively for the pre-test and post-test scanning sessions. LMEM analyses (with random intercepts by-participants) were used to analyze the hit rates and RT during the symbol trials. For RT, there was no main effect of group nor an interaction of time point X group (all p's > 0.1), but there was a main effect of session, $p < 0.01$, indicating that participants were significantly slower to make responses during the post-training scanning session compared to the pre-training scanning session. The analysis of the hit rate paralleled the RT analyses, with no significant main effect of Condition or an interaction of time point X Condition (all p's > 0.1), but there was a marginal main effect of time point, $p \approx 0.07$, indicating a tendency toward a lower hit rate (i.e., more misses) at the post- relative to the pre-training time point.

Table 4-5. Hits, RT (on hits), and false alarm rates for the symbol detection task in the scanner at both pre- and post-training time points. T = Typing, V = Visual, W = Writing.

	hits		RT (hits)		false alarms	
	pre	post	pre	post	pre	post
T	91.3%	82.5%	569	662	0.9%	0.3%
V	96.6%	93.4%	538	620	0.4%	0.7%
W	94.8%	94.8%	552	554	0.9%	1.0%
mean	*94.7%*	*90.7%*	*556*	*617*	*0.7%*	*0.7%*

Notes on Interpreting the RSA Results

The following five sections present all of the significant clusters at the post-training time point, reflecting each of the five types of letter representations (low-level visual, higher-level visual, motoric, phonological, and amodal). These clusters reflect either significant effects for one of the groups (typing, visual, or Writing Conditions), or an interaction with one of the behavioral measures (letter recognition, letter naming, letter writing, or word reading)[13]. For each of those clusters the following information is presented: (1) the location and strength (t-value) of the peak voxel in each cluster, (2) the total cluster sizes (mm^3), and (3) an anatomical/functional label for the cluster locations, and (4).

Note: If two different effects are both given the same neuroanatomical label, this indicates that at least some of the significant voxels within those clusters are shared. In other words, two clusters with different labels necessarily share *zero* significant voxels, and two

[13] A full report of all significant clusters, including main effects (i.e., effects in common across learning conditions) and interactions between groups (e.g., typing versus writing), is presented in Appendix A.

clusters with the same label necessarily share at least one voxel. For example, a "L fusiform (medial)" and a "L fusiform (posterior)" cluster do not overlap, whereas any two "L fusiform (medial)" clusters at least partially overlap, regardless of what effect is being reported there.

1. Low Level Visual Representation (Pixel Overlap)

The clusters showing a significant relationship with low level visual representations (i.e., greater pixel overlap, more similar neural representations) are listed in the left panel of Table 4-6, for group-specific effects, and in the right panel of Table 4-6, for interactions with behavioral tasks. These are depicted in Figures 4-5 (group-specific effects) and 4-6 (behavioral interactions). In total, 10 distinct clusters showed some significant relationship with pixel overlap: L and R cerebellum, R posterior and middle fusiform gyrus, R calcarine sulcus, bilateral posterior cingulate cortex, L postcentral gyrus, R dorsal premotor cortex, L superior temporal gyrus, and L inferior frontal gyrus (pars opercularum).

Table 4-6. Clusters associated with lowlevel visual representations (pixel overlap). Left panel: group-specific effects. T = Typing, V = Visual. Right panel: interactions with behavioral measures. Recognition = Letter Recognition RT, Naming = Letter Naming RT, Writing = Writing Letters to Dictation Accuracy, Reading = Word Reading Accuracy. Cerb = cerebellum, PCC = posterior cingulate cortex, FG = fusiform gyrus, IFG = inferior frontal gyrus, dPMC = dorsal premotor cortex, PostCG = postcentral gyrus, STG = superior temporal gyrus.

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
T	-41	-66	-33	-4.34	33	L cerb
T	0	-39	21	-4.58	14	bilateral PCC
T	42	-78	-17	-3.67	20	R post FG
V	-48	10	2	-4.42	16	L IFG operculum

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
Recognition	26	5	48	-5.27	35	R dPMC
Naming	-41	16	2	4.61	20	L IFG operculum
Writing	42	4	52	3.92	12	R dPMC
Reading	4	-71	10	4.22	24	R calcarine sulcus
Reading	-68	-20	22	4.36	16	L PostCG
Reading	-56	9	-3	4.52	16	L STG
Reading	46	-62	-21	3.86	20	R middle FG

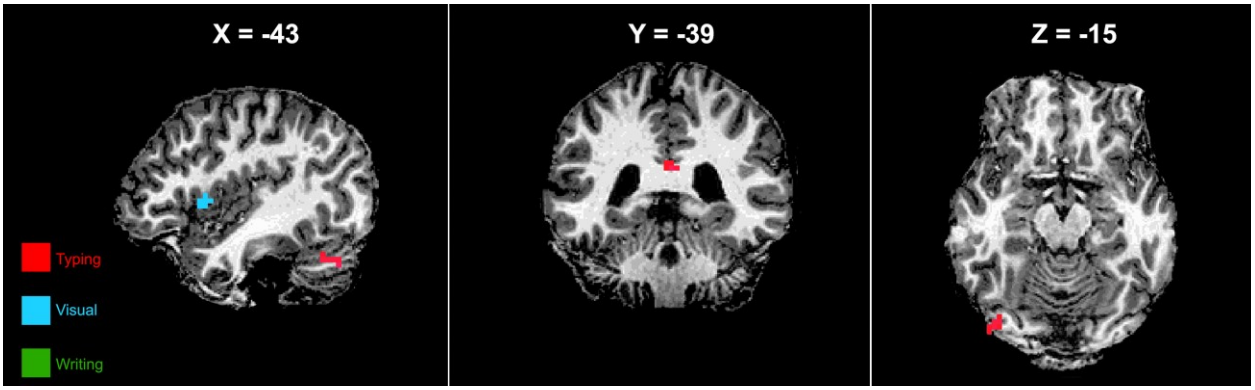

Figure 4-5. Significant group-specific effects of low level visual representations. MNI coordinates are labeled on the top. Right is on the left. Red = Typing Condition, Blue = Visual Condition.

Group-specific effects: The Typing Condition showed effects in L cerebellum, bilateral posterior cingulate cortex, and R posterior fusiform gyrus. The Visual Condition showed effects in L IFG (pars opercularis). All of these effects were positive relationships, with greater pixel overlap associated with greater neural similarity.

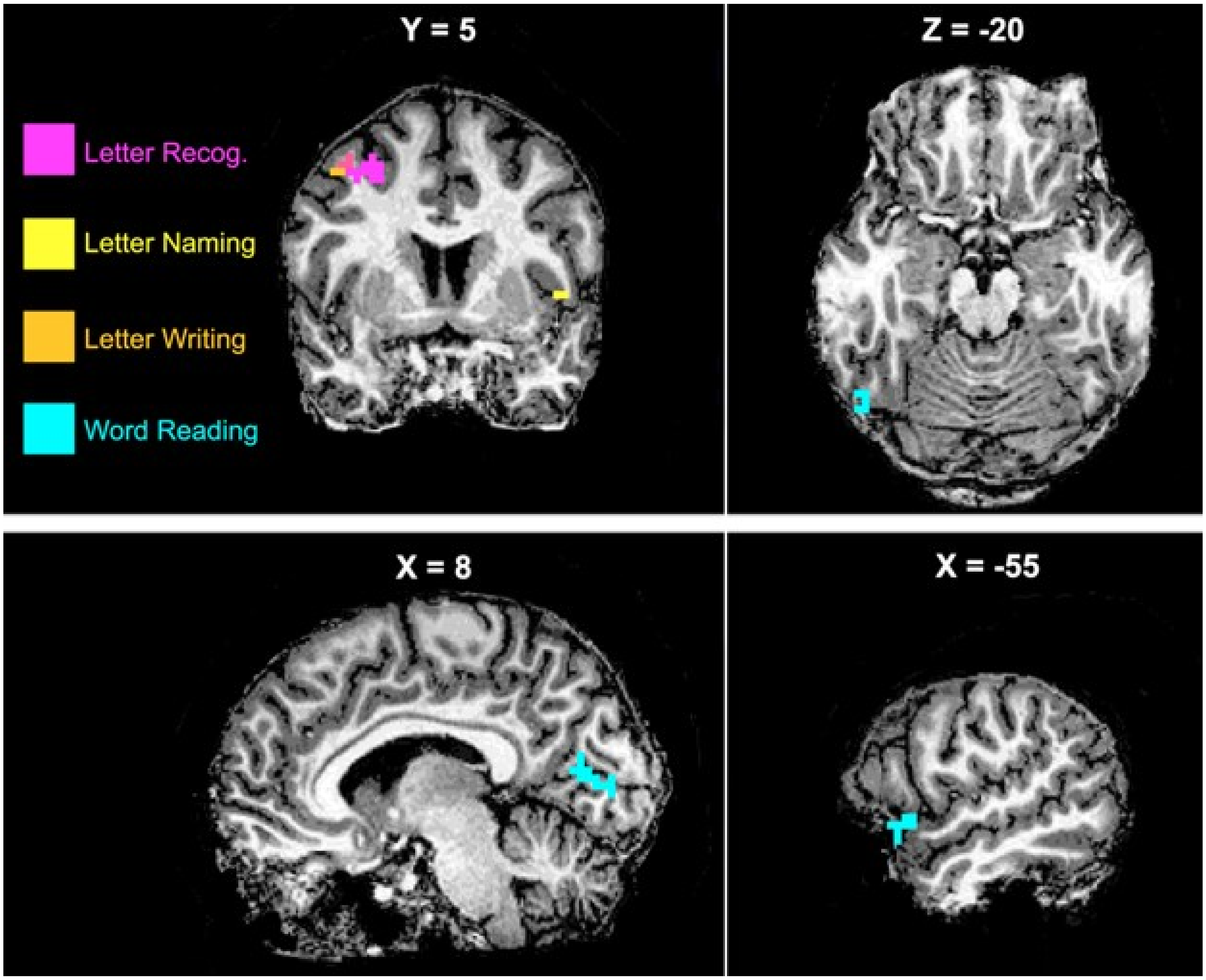

Figure 4-6. Significant interactions between behavioral measures and low level visual representations. MNI coordinates are labeled on the top. Right is on the left. Pink = Letter Recognition RT, Yellow = Letter Naming RT, Orange = Writing Letters to Dictation Accuracy, Teal = Word Reading Accuracy.

Behavioral measure interactions: A more positive relationship (greater pixel overlap associated with greater neural similarity) was found to be associated with faster RT on letter naming in one cluster: the L IFG (pars opercularum). All other interactions with behavioral measures were *negative*: more positive relationships between pixel overlap and neural similarity were associated with slower letter recognition in the R dorsal premotor cortex, as was lower accuracy on writing letters to dictation. A negative interaction was also found between pixel overlap and reading accuracy in four clusters: L superior temporal gyrus, L postcentral gyrus, R calcarine sulcus, and R middle fusiform gyrus.

Summary & Discussion: Low Level Visual Representations

Pixel overlap, a measure of low-level visual similarity, was found to be predictive of neural responses in a number of regions. In terms of the learning Condition, group-specific effects, all of the associated ROIs showed a positive relationship, indicating that pairs of letters overlapping more in pixels had more similar neural representations. This representation was most common for the Typing Condition, as participants in that group showed pixel overlap effects in three clusters, compared to just one for the Visual and none for the Writing Conditions.

In terms of the behavioral measures, pixel overlap was found to be associated with performance on all four tasks in at least one cluster. Strikingly, a more positive relationship with pixel overlap was associated with better performance in only one ROI: L IFG (pars opercularis) for the letter naming task. Individuals who were faster at letter naming showed a more positive association with pixel overlap-based representations. Moreover, this L IFG cluster overlaps heavily with that found for the Visual Condition where the effect was in the same direction.

For the most part, better performance on behavioral measures was found to be associated with *more negative* pixel overlap-based representations: all 4 of the clusters associated with reading accuracy, as well as the R dorsal premotor cortex cluster associated with both letter recognition and writing. A plausible explanation for this is that reliance on low-level visual representations in those brain areas is less effective for letter recognition and word reading. In other words, a strong low-level visual representation is not necessarily beneficial, and may be more present among individuals who perform worse, whereas those who perform better rely on other types of representations or other brain areas. Not mutually exclusive is the possibility that those who performed better on the behavioral tasks have a qualitatively different relationship between the predicted pixel overlap representation and the observed neural representation—this is suggested by the finding that those who performed best in fact had a *negative* association between pixel overlap and their neural activity.

To illustrate this possibility, an example is drawn from one of the clusters with a significant interaction between the pixel overlap predictor and the predictor measuring behavioral performance on the word reading task (in the right calcarine sulcus). **This interaction indicates that the association between the neural representation and the pixel overlap representation differed across individuals according to how well they performed on the word reading task.** Figure 4-7 depicts this interaction by plotting the LMEM's predicted neural similarity[14] between pairs of letters (y-axis) as a function of the amount of pixel overlap between those letters (x-axis). In this example, the LMEM revealed that greater pixel overlap was associated with more similar neural representations among, individuals who performed worse on the word reading task (blue line)—a positive association. However, among individuals who performed better on the word reading task

[14] LMEM, like all regression methods, can be used to generate predicted values of the dependent measure, given the fitted parameters (e.g., beta estimates). These predicted measures thus represent expected values of the dependent measure given independent measures, plus error (i.e., there is uncertainty around the predicted measure).

(yellow line), greater pixel overlap was associated with *less similar* neural representations—a *negative* association (akin to an anti-correlation).

This example highlights two important points. First is that the direction of the relationship distinguished between low and high-performers, and as such provides information about how a pixel overlap-based representation relates to behavior. In this example from the right calcarine sulcus, participants whose neural response was more similar to letters sharing more pixels performed *worse* on word reading. It is not the case, however, as can be seen in Figure 4-7, that individuals who performed the best had neural responses that were *unrelated* to pixel overlap. This relates to the second important point: sensitivity to some dimension of letter information (in this case, low-level visual information) is not necessarily reflected in neural responses that treat similar letters more similarly. Alternatively, it may be reflected in neural representations that treat similar letters significantly more *differently*. In either case, these results reflect some association between the type of letter information and the brain's response in that region of cortex. Moreover, the direction of this association provides useful information—in the example presented here, it does so by differentiating between low- and high-performers. Elsewhere, as is reported in the following sections, it can also differentiate participants who had writing training from those who did not.

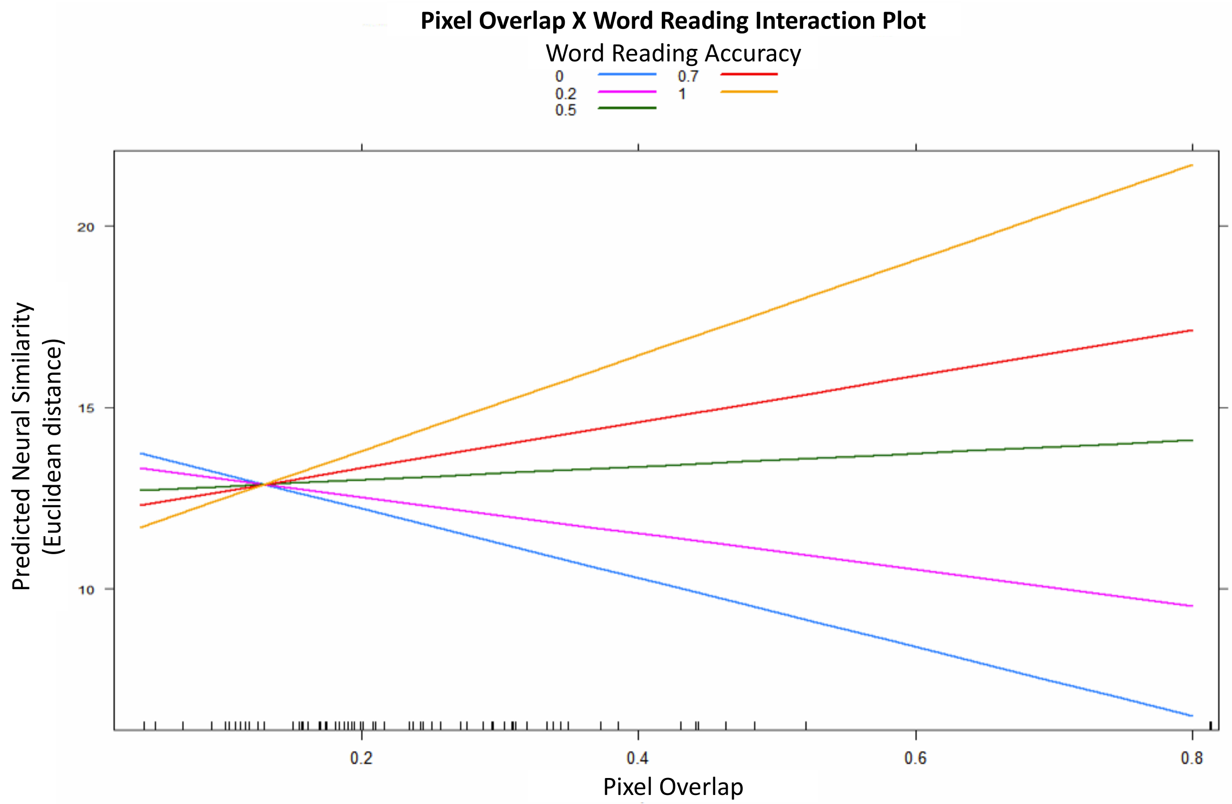

Figure 4-7. Effects plot of the interaction between low level visual representations and word reading accuracy, based on the LMEM analysis of the peak voxel in the R calcarine sulcus cortex. X-axis: pixel overlap, Y-axis: neural similarity measure (Euclidean distance, with greater distance indexing less neural similarity). Individuals with the highest behavioral performance on the word reading task outside of the scanner (yellow line) are predicted to have a negative relationship between pixel overlap and neural similarity (greater pixel overlap = greater neural distance, i.e., less similar neural representations), whereas those with the worst performance (blue line) are predicted to have a positive relationship (greater pixel overlap = less neural distance, i.e., more similar neural representations).

One critical fact to keep in mind is that these results are based on brain activation patterns during the simple symbol detection task (SDT) and *not* during the actual behavioral tasks, which were administered outside of the scanner prior to the post-training fMRI session. This makes the findings more powerful, in that they reveal that the neural activity in response to viewing single letters during the (very easy) symbol detection task is in fact predictive of behavioral performance on more complex tasks involving letter processing. However, this also means some caution should be taken when interpreting the results, because they cannot be taken as showing that these representations are actually active in these brain regions *during* the behavioral task. The conservative interpretation is that individuals whose neural activity is most similar to low-level visual representations tend to do worse on letter processing tasks. And, paralleling the results of the behavioral same/different letter judgment, the pixel overlap-based representation is seen primarily in those who had typing training, not those who had writing or visual training. This is consistent with the generally poorer performance of typing training on measures of learning generalization, and suggests part of this is due to reliance on the low-level visual information (which, notably, was the only type of letter representation found to influence letter perception at the *pre-training* time point).

2. Higher Level Visual Representation (Visual Features)

The clusters showing a significant relationship with higher level visual representations (i.e., more shared visual features, more similar neural representations) are listed in Table 4-7: with group-specific effects in left panel and for interactions with behavioral tasks in the right panel. These are depicted in Figures 4-8 (group-specific effects) and 4-9 (behavioral interactions). All of these clusters showed *negative* associations. In total, 15 distinct clusters showed some significant relationship with visual features: L V5/MT, L inferior frontal gyrus (operculum), L middle & posterior fusiform gyrus, L inferior temporal gyrus, L middle frontal gyrus (Brodmann Area 6), L supramarginal gyrus, L superior parietal lobule, L precentral gyrus (two clusters, one superior), L dorsolateral prefrontal cortex, L precuneus, R ventrolateral prefrontal cortex, R middle fusiform gyrus, and R lateral occipital sulcus.

Table 4-7. Clusters associated with higher-level visual representations (visual features). Left panel: group-specific effects. V = Visual, W = Writing. Right panel: interactions with behavioral measures. Recognition = Letter Recognition RT, Naming = Letter Naming RT, Writing = Writing Letters to Dictation Accuracy, Reading = Word Reading Accuracy. MT = middle temporal, IFG = inferior frontal gyrus, ITG = inferior temporal gyrus, MFG6 = middle frontal gyrus/Brodmann Area 6, SMG = supramarginal gyrus, PreCG = precentral gyrus, SPL = superior parietal lobule, DLPFC = dorsolateral prefrontal cortex, VLPFC = ventrolateral prefrontal cortex, LOS = lateral occipital sulcus.

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
V	-53	-75	-3	3.64	14	L V5/MT
V	-53	13	6	5.42	26	L IFG operculum
V	-47	-68	-8	4.96	62	L middle & posterior fusiform, L ITG
V	-44	-6	39	3.58	13	L MFG6
V	-43	-52	51	5.25	39	L SMG
V	46	-69	-2	4.59	34	R middle fusiform
W	-57	-7	7	4.24	11	L PreCG
W	-50	8	17	5.225	14	L PrecG (superior)
W	-29	-67	46	4.26	12	L SPL

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
Recognition	-53	-71	-2	-3.86	10	L V5/MT
Recognition	-53	4	11	-3.82	16	L PreCG
Recognition	-50	10	25	-4.19	28	L PrecG (superior)
Recognition	-41	-81	-13	-5.21	27	L posterior fusiform
Recognition	-36	25	22	-3.82	19	L DLPFC
Recognition	-11	-69	38	-3.4	15	L precuneus
Recognition	41	40	7	-4.78	13	R VLPFC
Recognition	43	-93	2	-4.23	9	R LOS
Naming	-55	11	14	-4.03	19	L PreCG, L PrecG (superior)
Naming	-44	18	-1	-4.58	28	L IFG operculum
Reading	-48	-42	55	5.56	64	L SMG
Reading	-48	25	23	4.25	15	L DLPFC
Reading	-48	25	23	4.25	15	L DLPFC
Reading	-44	6	25	4.68	21	L PrecG (superior)
Reading	-14	-67	38	5.21	30	L precuneus
Reading	-43	-77	-19	5.57	27	L posterior fusiform

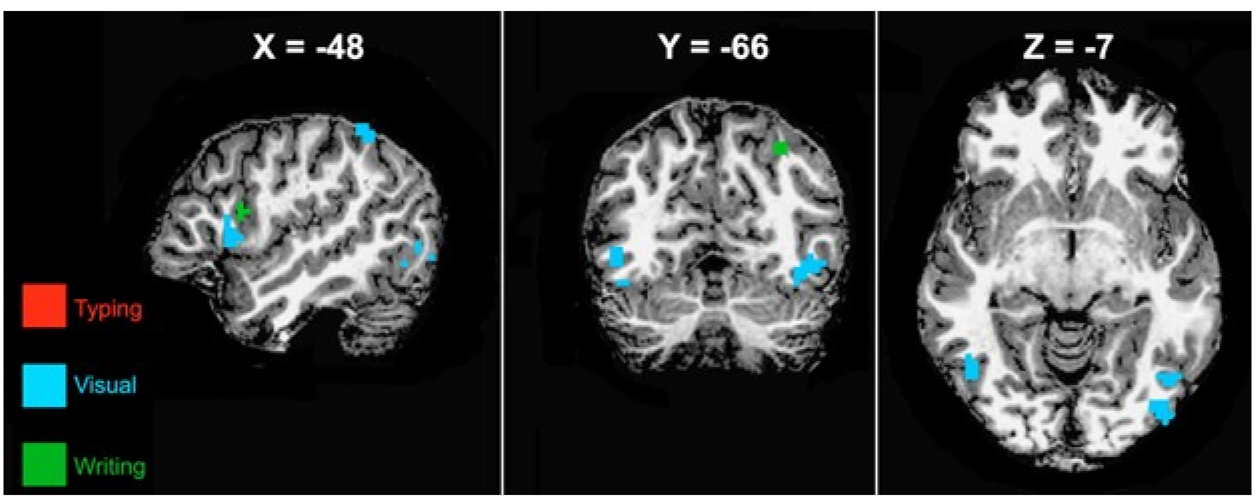

Figure 4-8. Significant group-specific effects of higher level visual representations. MNI coordinates are labeled on the top. Right is on the left. Blue = Visual Condition, Green = Writing Condition.

Group-specific effects: The Visual Condition showed effects in L V5/MT, L IFG operculum, L middle & posterior fusiform gyrus, L MFG (Brodmann Area 6), L supramarginal gyrus, and the R middle fusiform gyrus. The Writing Condition showed effects in L two separate clusters in the precentral gyrus, and the L superior parietal lobule. All these effects were negative associations.

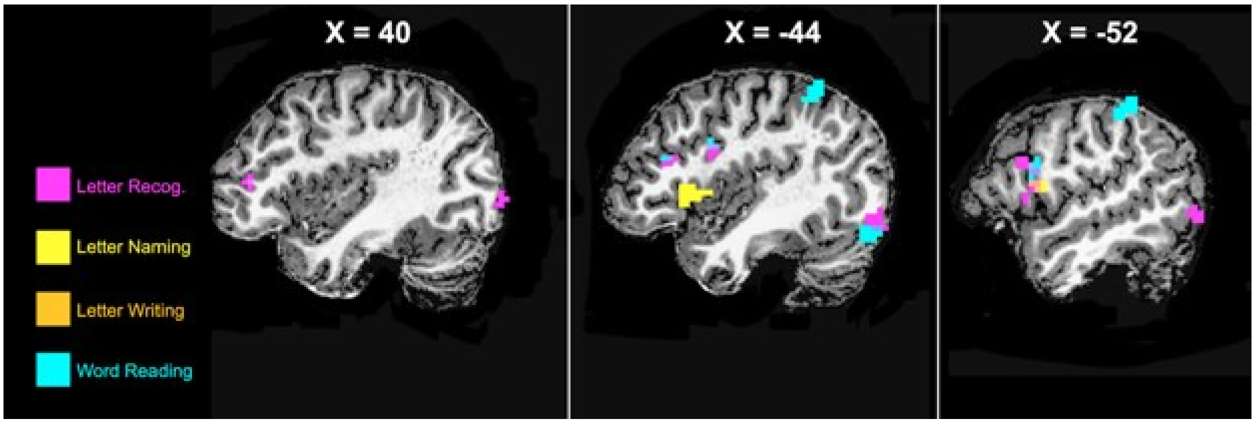

Figure 4-9. Significant interactions between behavioral measures and higher level visual representations. MNI coordinates are labeled on the top. Right is on the left. Pink = Letter Recognition RT, Yellow = Letter Naming RT, Orange = Writing Letters to Dictation Accuracy, Teal = Word Reading Accuracy.

Behavioral measure interactions: Better performance on the behavioral measures was associated only with more strongly *negative* associations with the neural representations. Specifically, faster RT on letter recognition was associated with more strongly negative associations in 8 clusters: L V5/MT, R lateral occipital sulcus, L posterior fusiform, L precuneus, two clusters in the L precentral gyrus, L DLPFC and R VLPFC. Likewise, faster RT on letter naming was associated with more strongly negative associations in the same two precentral gyrus clusters as well as in the L opercular cortex. Finally, better accuracy on reading was associated with more strongly negative relationships in the same (superior) L precentral gyrus cluster, the L precuneus cluster, the L posterior fusiform cluster, the L supramarginal gyrus, and L DLPFC.

Summary & Discussion: Higher Level Visual Representation

As a striking counterpoint to the low-level visual representations (pixel overlap), the higher-level visual representation measured by the proportion of shared visual features were exclusively negatively associated with neural representation. Without any exceptions, all effects suggested that pairs of letters with more visual features in common in fact tend to have *less* similar neural patterns of activation.

A large number of clusters (10) were found to be related to three of the four behavioral measures: letter recognition, letter naming, and word reading, and all three of these measures showed that those who performed best had less similar neural representations for stimuli that share more visual features. A comparison of the results for pixel overlap with those here for visual features reveals just two clusters in common, R middle fusiform gyrus and L IFG (operculum). Primarily the results are distinct—including the fact that the direction of the relationships tended to be opposite for the two measures, despite the two predicted similarity measures being themselves positively correlated (i.e., higher pixel overlap correlates positively with a higher proportion of shared features, $r = 0.769$).

Lastly, the Typing Condition did not show any evidence of visual feature representations. This also contrasts with the results of pixel overlap, where the Typing Condition was predominant. This means that the clusters showing apparently desirable associations for performance on letter recognition, naming, and word reading overlapped with some clusters unique to the Visual Condition (naming in L IFG, recognition in L V5/MT and L posterior fusiform) and the Writing Condition (naming, recognition, and word reading in the L precentral gyrus), but nothing for the Typing Condition.

All of the effects showed negative associations—letters sharing more visual features had less similar neural representations. One way this could be explained is if only distinctive features were represented and/or attended to (for an explanation of how this could lead to a *negative* association see Appendix B). In fact, research into the differences between naïve and expert letter perception has revealed that one of the hallmarks of expert letter processing is a greater influence of what makes a letter distinctive, relative to the set of alternative letters (Wiley and Rapp, under review). This is not surprising, given that successful letter identification hinges upon recognizing when a token of a letter is a representation of its type—variations in font and handwriting must be abstracted away from, which is presumed to be achieved by identifying the underlying visual features. Additional evidence that experts attend to only critical portions of letter stimuli comes from use of the "Bubbles" technique (Fiset et al., 2009, 2008; Hannagan & Grainger, 2013), revealing that in the Roman alphabet, successful letter identification is based on only certain portions of the letter-shapes.

Setting aside the nature of the negative direction of the associations, the visual features results reveal once again a striking degree of consistency with the behavioral findings, in terms of the strengths and weaknesses of the learning condition. Moreover, the results yet again are suggestive of how the differences in behavior may be tied to different cognitive representations, and access to these representations. As with the results of low-level visual similarity, the Typing Condition was shown to be the most lacking in supporting representations that were associated with better letter processing abilities. In both bilateral vOTC and L inferior frontal/precentral gyrus areas, the Typing Condition showed weaker effects than the visual and Writing Conditions. Overall, the Visual Condition showed the most widespread effects (the most distinct clusters), although the Writing Condition showed effects in areas that also related to three of the behavioral tasks (naming, recognition, and reading) compared to just two for the Visual Condition (naming and recognition).

3. Motoric Representation (Motor Bistrokes)

The clusters showing a significant relationship with motoric representations (i.e., more shared motor bistrokes, more similar neural representations) are listed in the left panel of Table 4-8, for group-specific effects, and in the right panel of Table 4-8, for interactions with behavioral tasks. These are depicted in Figures 4-10 (group-specific effects) and 4-11 (behavioral interactions). In total, 30 distinct clusters showed some significant relationship with motoric representations, 25 positively associated and 5 negatively associated.

Table 4-8. Clusters associated with motoric representations (motor bistrokes). Left panel: group-specific effects. T = Typing, V = Visual, W = Writing. Right panel: interactions with behavioral measures. Recognition = Letter Recognition RT, Naming = Letter Naming RT, Writing = Writing Letters to Dictation Accuracy, Reading = Word Reading Accuracy. MT = middle temporal; DLPFC = dorsolateral prefrontal cortex, ITG = inferior temporal gyrus, SMG = supramarginal gyrus, IFG = inferior frontal gyrus, PreCG = precentral gyrus, FG = fusiform gyrus, FEF = frontal eye fields, ACC = anterior cingulate cortex, meSFG = medial superior frontal gyrus, cerb = cerebellum, LOS = lateral occipital sulcus, IPS = intraparietal sulcus, IPL = inferior parietal lobule, postCG = postcentral gyrus, PCC = posterior cingulate cortex, MFG6 = middle frontal gyrus (Brodmann area 6), STG = superior temporal gyrus, VLPFC = ventrolateral prefrontal cortex.

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
T	-51	-75	2	-4.41	25	L V5/MT
T	42	-67	-5	-3.91	13	R V5/MT
V	-48	34	32	-4.801017	16	L DLPFC
V	-46	-67	-6	-4.43	10	L ITG
V	-44	-48	55	-6.420595	83	L SMG
V	-44	22	26	-5.988792	142	L IFG, L PreCG, PreCG (sup.), L DLPFC
V	-41	-67	-14	-4.33	18	L mid FG
V	-38	-85	-12	-4.06	12	L post. FG
V	-32	0	33	-6.546516	61	L FEF
V	-15	-68	39	-5.868388	25	L precuneus
V	-11	-18	36	-5.465593	12	L cingulate sulcus
V	-8	11	24	-5.19948	20	L ACC
V	-3	30	40	-5.362441	87	bilateral meSFG
V	-3	37	35	-4.314883	14	L anterior meSFG
V	12	-64	40	-4.723657	32	R precuneus
V	21	-72	-31	-6.673416	26	R cerb (post. inf.)
W	-34	-93	-1	-3.86	14	L LOS
W	-23	-79	39	-5.21	43	L post. IPS
W	33	-65	-26	-4.59	12	R cerb (post.)
W	48	-71	-17	-5.16	31	R post. FG
W	36	-44	40	4.82	16	R anterior IPS/R IPL
W	49	-63	-10	-4.86	13	R mid FG

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
Recognition	-63	-20	24	3.945317	13	L post.CG
Recognition	-41	14	-3	4.407196	12	L IFG operculum
Recognition	-39	-84	-14	5.2	63	L anterior, mid & post. FG, L ITG
Recognition	-23	-76	37	4.667494	12	L post. IPS
Recognition	-9	-65	37	5.445757	25	L precuneus
Recognition	-5	20	43	4.275994	38	bilateral meSFG
Recognition	3	-39	26	5.336084	19	bilateral PCC
Recognition	28	13	45	5.060601	22	R MFG6
Recognition	42	-68	-5	-4.89	12	R V5/MT
Recognition	45	-50	43	-3.696916	11	R anterior IPS/R IPL
Naming	-56	13	-9	5.303112	15	L STG
Naming	-54	10	15	4.40964	25	L preCG (sup.)
Naming	-47	14	7	4.919203	29	L IFG operculum
Naming	-39	25	22	4.148455	13	L DLPFC
Naming	-11	-68	37	5.038149	29	L precuneus
Naming	13	-73	43	3.790202	23	R precuneus
Writing	-48	12	16	-4.5	20	L preCG (sup.)
Writing	-39	-56	-9	-4.14	27	L anterior FG
Writing	40	31	23	5.01	25	R DLPFC
Writing	42	3	3	4.5	15	R VLPFC
Reading	-46	-47	55	-7.714195	76	L SMG
Reading	-45	-53	-11	-3.81	16	L anterior FG
Reading	-43	-78	-19	-3.69	12	L post. FG
Reading	-41	-70	-5	-3.49	9	L mid FG
Reading	-41	7	35	-4.413876	51	L preCG (sup.), L FEF
Reading	-9	-65	38	-6.539762	37	L precuneus
Reading	1	34	32	-4.621985	38	bilateral meSFG
Reading	13	-67	38	-4.360747	21	R precuneus
Reading	42	-65	-13	-3.91	10	R mid FG

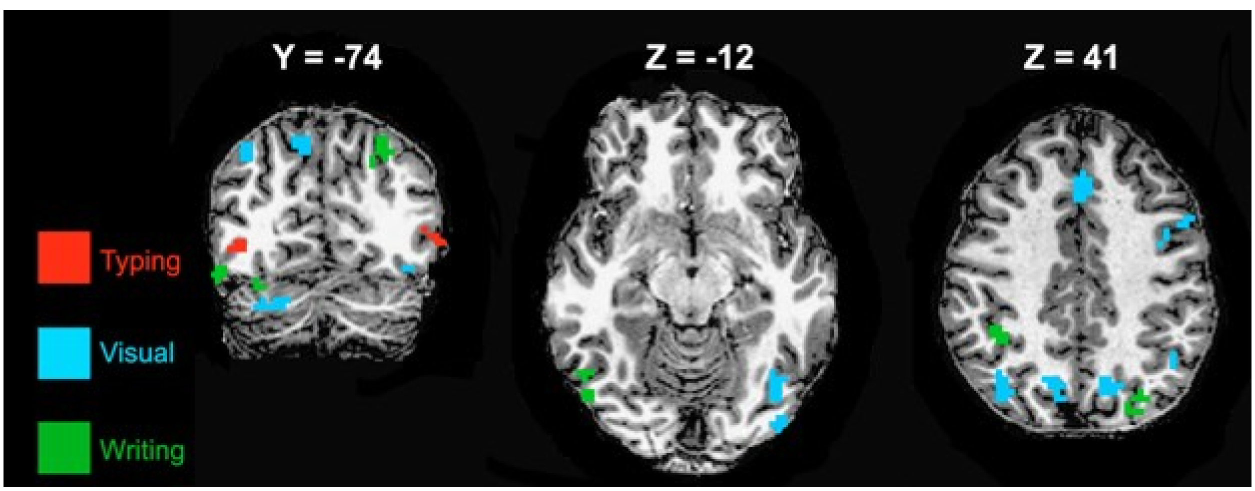

Figure 4-10. Significant group-specific effects of motoric representations. MNI coordinates are labeled on the top. Right is on the left. Red = Typing Condition, Blue = Visual Condition, Green = Writing Condition.

Group-specific effects: The Typing Condition showed effects in 2 clusters, bilaterally around area V5/MT. The Visual Condition showed effects in 17 clusters: L DLPFC, L inferior temporal gyrus, L supramarginal gyrus, L IFG (operculum), both clusters in the L precentral gyrus, L middle and posterior fusiform gyrus, L frontal eye fields, L and R precuneus, L cingulate sulcus, L anterior cingulate cortex, bilateral medial superior frontal gyrus, L anterior superior frontal gyrus, and R cerebellum (posterior-inferior cluster). The Writing Condition showed effects in 7 clusters: L lateral occipital sulcus, L posterior intraparietal sulcus, R cerebellum (posterior cluster), R middle and posterior fusiform gyrus, R anterior intraparietal sulcus, and R inferior parietal lobule. All of these effects were positive association, with the exception of the writing experience effects in the R anterior IPS and R inferior parietal lobule.

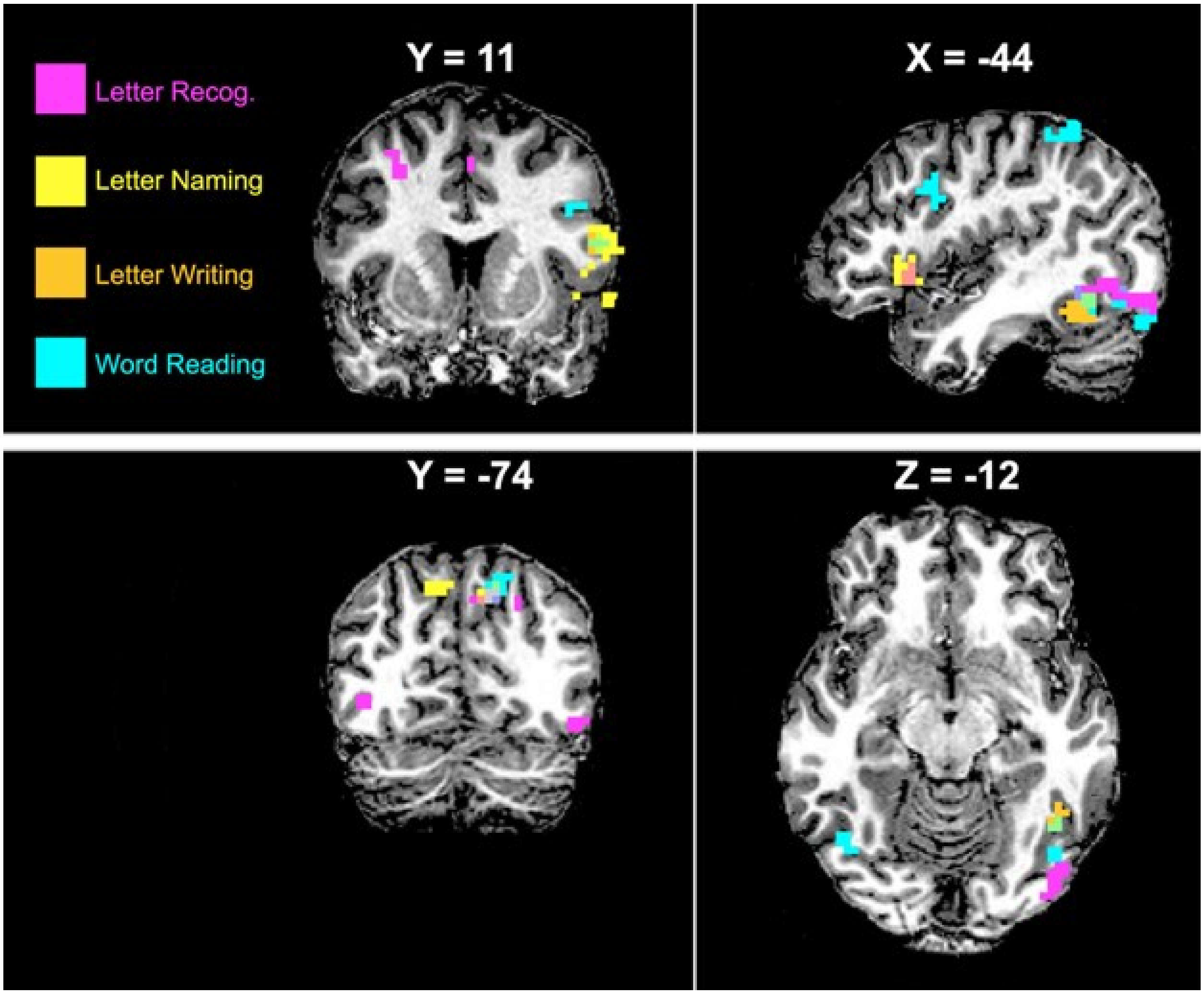

Figure 4-11. Significant interactions between behavioral measures and motoric representations. MNI coordinates are labeled on the top. Right is on the left. Pink = Letter Recognition RT, Yellow = Letter Naming RT, Orange = Writing Letters to Dictation Accuracy, Teal = Word Reading Accuracy.

Behavioral measure interactions: Faster RT on letter recognition had more positive associations with motoric representations in 10 clusters: 3 clusters spanning the length of the L fusiform gyrus, L precuneus, L inferior temporal gyrus, L IFG (opercular part), L postcentral gyrus, L posterior IPS, bilateral medial superior frontal gyrus, and R MFG (Brodmann Area 6). Faster RT on letter naming likewise was positively associated with motoric representations in 6 clusters: overlapping parts of the L IFG (opercular part) and L precuneus, as well as the R precuneus, L precentral gyrus (superior cluster), L superior temporal gyrus, and L dorsolateral prefrontal cortex. Better accuracy on writing letters was positively associated in the L precentral gyrus (superior cluster) and in L anterior fusiform gyrus. Finally, better accuracy on word reading was positively associated in 10 clusters: the L precentral gyrus (superior cluster) and L precuneus, L frontal eye fields, L fusiform gyrus (all 3 clusters), R mid fusiform gyrus, L supramarginal gyrus, and bilateral medial SFG.

In contrast, 5 clusters related to behavioral measures in the opposite direction, with better performance *negatively* associated letter recognition in R V5/MT, R anterior IPS, and R inferior parietal lobule, and with letter writing in R both ventro- and dorsolateral prefrontal cortex.

Summary & Discussion: Motoric Representation

There are several prominent results to highlight from the analyses of motor features. The extent of clusters showing sensitivity to this representational type was the most extensive, covering most of the regions in the combined LLN-vOTC search space. This is surprising, given that only one third of the participants had much writing experience with the Arabic letters. While certainly it is possible that all of the participants developed motoric representations (and they generally were all able to complete the writing letters to dictation task; see Chapter 3), these were expected to be strongest among the Writing Condition participants. On the contrary, the Writing Condition actually showed fewer clusters reflecting motoric representations, whereas the Visual Condition showed the most. However, a closer inspection of the evidence supports the conclusion that many of these clusters in fact reflected visual dynamic representations, and not motoric ones.

This is so first of all because the clusters where the Writing Condition showed motoric representations were largely unrelated to other types of information (i.e., low level or higher level visual). Of the 7 Writing Condition clusters reported here, in none of them did participants in that group show visual representations as whole. In terms of the interactions with behavioral measures, only in the R middle fusiform cluster was there found an association with visual information (in relation to letter recognition RT).

This contrasts with the other two training Conditions. First, the Typing Condition showed just two motoric clusters. However, their location is *highly* indicative of dynamic visual information. These clusters lie in part of extrastriate cortex in the lingual gyrus, including the likely site of area V5/medial temporal (MT), also known as the human motion complex (Dumoulin, 2000; Kriegeskorte et al., Goebel, 1993). In fact, this area has been associated not only with letter processing, but also the processing of visual motion and action perception, And in fact, the R V5/MT motoric cluster also showed an interaction with letter recognition RT (a negative one, indicating that a motoric representation such as the Typing Condition showed was "undesirable" for fast letter recognition).

Second, although the Visual Condition showed a large number of motoric clusters (16 in total), these were almost entirely associated with other types of information, Seven of them were previously reported (Table 4-7) because the same participants simultaneously showed evidence of higher level visual representations in the same voxels. Five more were also reported as showing interactions between visual representations and behavioral measures—notably, excluding the writing to dictation task.

The inference to be drawn here is that the "motoric representations" found among the Typing and Visual Conditions are very likely, although not definitely, reflecting visual dynamic representations. This is so both because of what is known about what processes those areas are typically implicated in, and because the RSA results of this chapter also substantiated visual representations in many of the same clusters. This contrasts with the Writing Condition, where only 1 out of 7 clusters were similarly associated with visual information.

4. Phonological Representation (Letter Names)

Only one significant cluster was found to relate to letter names: in the L superior temporal gyrus, there was a positive association with the letter name similarity (i.e., more shared phonological features in the letter names, more similar neural representations), a Typing Condition-specific effect (Table 4-9).

Table 4-9. Cluster positively associated with letter name representations. STG = superior temporal gyrus. T = Typing.

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
T	-53	15	-3	-4.35	19	L STG

Summary & Discussion: Phonological Representation

There was scant evidence of phonological representations: only one cluster, which showed a Typing Condition-specific effect. This cluster overlaps extensively with 3 clusters previously reported: one showing a positive association between low level visual representation and word reading (MNI peak: -56, 9, -3), one showing a positive association with motoric representation (MNI peak: -54, 9, -5), and one showing a positive association between motoric representation and letter naming (MNI peak: -56, 13, -9). These clusters cover an anterior portion of the superior temporal gyrus and extend into the lateral sulcus and most inferior and lateral portions of the inferior frontal gyrus.

There are at least two possibilities for why there was a relative dearth of evidence for letter name representations. The first is that the characterization of letter name similarity, based on the phonological features of the letter names (see Chapter 2, section III. "Behavioral Analyses"), was perhaps not sufficiently similar to the representations actually present in the brain. The more interesting possibility is related to the fact that, as previously pointed out, in the scanner the participants were performing only a basic symbol detection task—thus, it may be the case that regions that would be activated for the actual letter naming task and that would show letter name representations in an RSA analysis were not responding this way during the scanner task.

One might wonder why motoric representations were found to be widely represented but not letter names, even though both types of information would seem to be equally irrelevant to the symbol detection task. However, at least some of the clusters responsive to motor features may in fact have been representing visual information (see last section), albeit dynamic instead of static (the scanner stimuli were static). Moreover, it has been well-established that orthographic stimuli activate premotor and supplementary motor areas even during passive viewing tasks (James & Gauthier, 2006; James, Jao, & Berninger, 2015; Longcamp et al., 2003; Longcamp, Tanskanen, et al., 2006), and motor knowledge may be particularly activated by chirographic/cursive stimuli, such as were the Arabic letter stimuli in this experiment (Kersey & James, 2013; Li & Yeh, 2003). There is no corresponding evidence of such strong and consistent activation of auditory cortex during passive letter viewing, and in fact auditory/phonological processing cortices were not included in the LLN (with the possible exception of this small cluster in left STG), unlike the supplementary motor and premotor areas. This is plausibly due to the fact that motoric representations and visual representations are necessarily related to one another, whereas the relationship between a letter's shape and its name is completely arbitrary, and therefore recruiting motoric information is more likely to help visually recognize a letter than is phonological information.

5. Amodal Representation: Symbolic Letter Identity (SLI)

The significant clusters showing a positive association with the SLI (i.e., shared identity/allographs, more similar neural representations) are listed in Table 4-10, and depicted in Figure 4-12. No clusters showed a negative association. In total, 3 clusters showed some significant relationship with SLI: L precentral gyrus, bilateral pre-SMA, and R lateral occipital sulcus.

Table 4-10. Clusters associated with symbolic letter identity (SLI) representations. PreCG = precentral gyrus, SMA = supplementary motor area, LOS = lateral occipital sulcus. T = Typing, V = Visual, W = Writing. TvV = Typing versus Writing, VvW = Visual versus Writing. Recognition = Letter Recognition RT.

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
Recognition	-50	10	12	3.28	11	L PreCG
TvW	-57	7	9	3.9	15	L PreCG
TvW	3	10	59	4.46	19	bilateral pre-SMA
VvW	1	11	59	4.22	18	bilateral pre-SMA
W	-57	7	9	3.9	14	L PreCG
W	1	12	61	3.49	16	bilateral pre-SMA
W	40	-85	2	3.86	9	R LOS

Group-specific effects: The Writing Condition alone showed significant effects in 3 clusters: L precentral gyrus, bilateral pre-SMA, and R lateral occipital sulcus. The Writing Condition differed significantly from the Typing Condition in the L precentral gyrus ad pre-SMA clusters, and from the Visual Condition in the pre-SMA cluster.

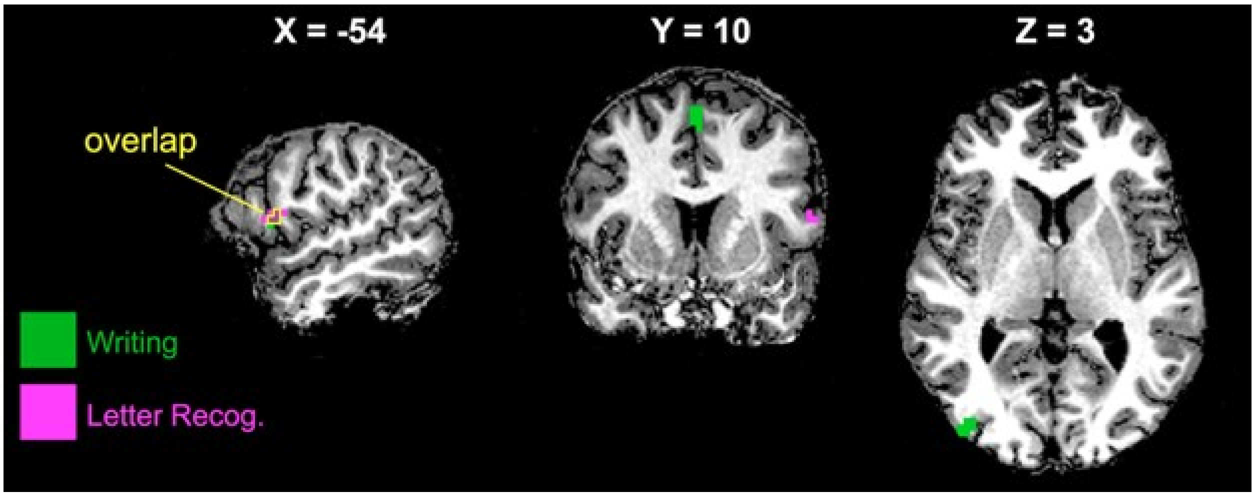

Figure 4-12. Significant clusters associated amodal SLI representations. MNI coordinates are labeled on the top. Right is on the left. Pink = Letter Recognition RT, Green = Writing Condition.

Behavioral measure interactions: RT on the letter recognition task was positively associated with the strength of SLI representations in the L precentral gyrus cluster.

Summary & Discussion: Amodal Representation

Strikingly, the only significant effects were found for the Writing Condition. Moreover, these effects were significantly stronger than the Typing Condition in two clusters (L preCG and bilateral pre-SMA) and the visual experience in one (bilateral pre-SMA). The SLI representation also interacted with the behavioral measure of letter recognition, such that individuals who were faster showed stronger SLI representations, suggesting an advantage for the Writing Condition (and with typing-trained participants once again the worst off, as the Typing Condition showed significantly less of an SLI representation in this L preCG cluster).

The results here show that as a group, only the Writing Condition participants showed any evidence of the amodal representation of SLI. This mirrors their behavioral performance on the Same/Different Judgement task, although the Visual Condition also showed an effect of SLI on that task. In fact, the Visual Condition differed significantly from the Writing Condition in only the pre-SMA cluster, and not in the preCG cluster, whereas the Typing Condition differed significantly in both (see Appendix A).

The results are unequivocal in showing that the SLI representation is most apparent after writing training. Taken together with the behavioral evidence from the Same/Different Judgement task, these results present compelling evidence that amodal letter representations not only exist, but in fact were seen to arise most strongly among those who have writing experience. Each of the three clusters showing this amodal representation is discussed in turn with regard to the role that the representation may be playing in that region.

First, in addition to the Writing Condition-specific SLI representation, the R LOS cluster also showed an association between higher level visual representation and behavior on the letter recognition task (Table 4-7). The implication is that SLIs are used to support visual recognition processes in the R LOS, both because this region is considered part of the visual processing network and specifically shows sensitivity to shape (Braunlich, Gomez-Lavin, & Seger, 2015; Sawamura, Orban, & Vogels, 2006), and because the RSA results showed that both SLI and visual representations were activated here (presumably facilitating identification of the letter-shapes/allographs). It cannot be ascertained from this method whether or not the *same voxels*, much less the same neurons, are implicated in processing both SLI and visual information. Nonetheless, there are implications that the same substrates, grossly described, are seen to instantiate both modal and amodal representations—this is compelling evidence in favor of amodal representations that are not limited to "convergence zones" thought to reflect multimodal representations instead of amodal ones (see Barsalou, 2016; Binder, 2016).

Second, the pre-SMA has functional connections to brain regions that are implicated in higher-level cognitive processes underlying complex planning for motor and language tasks (Kim et al., 2010). The SLI representation could plausibly be implicated in such cognitive processes. This moreover would be expected to arise in this area with writing experience, especially so as the writing training involved transcoding the visual and/or phonological input (the letter name) into motor plans, and SLI is proposed to mediate between such transcoding (see Chapter 5). Moreover, because participants were taught allographs that require distinct motor plans, a certain amount of abstraction was required for writing to dictation task: presumably letter name input led to activation of *both* allographs/motor plans, which then had to be selected by further incorporating additional cues—either visual or other contextual cues, indicating which allograph needed to written.

Third, the cluster in the precentral gyrus overlapped[15] with the many other precentral gyrus clusters (including the superior ones, all depicted in Figure 4-13): as with

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[15] N.B.: The term "overlap" here is used to indicate that the multiple regression (the LMEM analyses) found simultaneous unique variance was explained by more than one representational type. In other words, "overlapping" clusters mean that some model(s) reported significant effects of more than one modality-specific or amodal representation.

the R LOS cluster, the Writing Condition also showed higher level visual representations in the L superior preCG cluster. The higher level visual representations in this area were also associated with letter recognition, letter naming, and word reading performance. There was also main effect of motoric representations in the L superior preCG cluster, which was also associated with performance on the Letter Naming, Writing Letters to Dictation, and Reading Word tasks (see Appendix A). This area in particular has been identified as part of the "visual-motor letter processing" system (James, 2017) associated with both letter perception and writing; perhaps most intriguing, it is one of the associative areas hypothesized to represent abstract concepts via multimodal compression (see Chapter 1), a possibility which is returned to in Chapter 5.

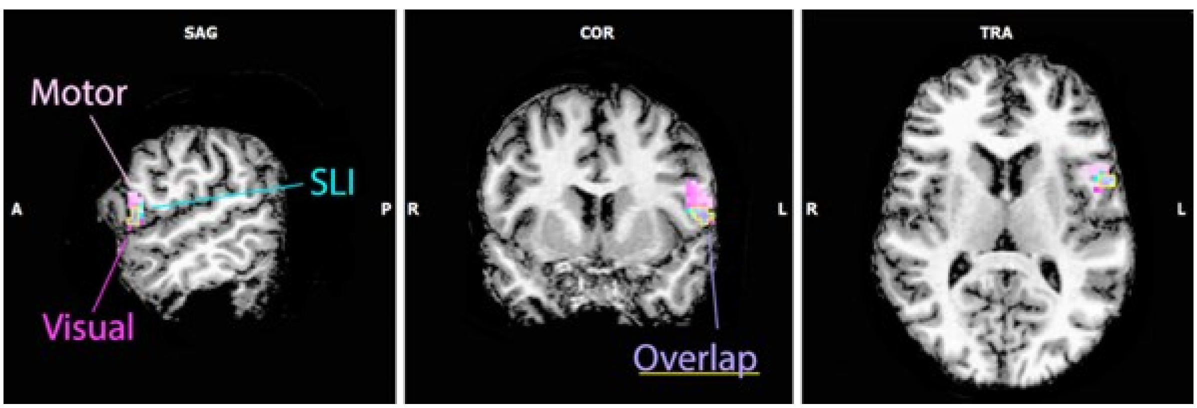

Figure 4-13. Precentral gyrus clusters (MNI coordinates: -57, 7, 10) showing multiple letter representations. Cluster overlap (purple voxels) outlined in yellow.

Altogether, the evidence supports the account that the generally superior performance of the Writing Condition, on both measures of generalization and retention, is associated with better learning of the symbolic letter identities. This is supported by both the behavioral and the neural letter representation results (i.e., the same/different task and the RSA). The findings are also consistent with the more mixed performance for the Visual

Condition and generally poorest performance for the Typing Condition. This pattern of results is contrary to the predictions of strong embodiment theory, which rejects amodal representations. At the same time, the fact that amodal representations were most strongly learned by those who had writing experience upholds the importance of writing for letter learning. The advantages of writing training over non-motor training was seen to be related primarily to superior letter recognition. Certain aspects of grounded cognition accounts are supported by these results—both visual and motoric representations were seen to underlie much of the brain activity during the symbol detection task, and crucially these representations were associated with behavioral performance on letter processing tasks. This, therefore, constitutes strong evidence that sensory/motor representations activated during letter perception are not epiphenomenal. However, we clearly find amodal representations do form part of the content of letter concepts, and likewise are implicated in letter processing behaviors. In addition, given that neither grounded cognition nor abstractionist predict that writing experience would support learning amodal representations in particular. These issues are discussed in the following chapter.

Chapter 5 – General Discussion

This chapter concludes that the evidence reported in this dissertation supports the view that cognition involves both groundedness and abstraction. Sensory/motor letter representations were found to be recruited for letter perception, and were associated with behavioral performance on letter processing tasks. However, motoric representations were not unique to individuals who had writing training. Furthermore, amodal letter representations, symbolic letter identities (SLIs), were also found to be associated with behavioral performance on letter processing tasks, and were most clearly present among individuals who had writing experience. Therefore, these results present a challenge both to embodiment theories that reduce concepts to sensory/motor representations, as well as to strong abstractionist claims that sensory/motor activity is epiphenomenal. On the basis of these results, I propose that the reason writing experience is particularly beneficial to learning letters is because it strengthens connections between various modality-specific letter representations that are mediated by amodal SLI representations. In addition to discussing the implications of these results for theories of cognition, practical implications for education and future directions for research are considered as well.

This following two sections review the results as they pertain to these issues. The first section (I. "How Does Writing Benefit Learning?") focuses primarily on the behavioral results, answering the first question of the dissertation. Establishing what the benefits of writing experience actually are is important for its practical implications, but also provides the measures of behavioral performance necessary for answering the other two key questions addressed in the dissertation. These are discussed in the second section of this chapter (II. “Multimodal and Amodal Letter Representations).

I. How Does Writing Benefit Letter Learning?

This section presents a final account of how writing training and non-motor training led to the learning of different letter representations and supported different behavioral abilities. A summary of the behavioral findings is presented in Table 5-1, and is used to guide discussion of the overall pattern of results.

Table 5-1. Summary of the behavioral results from Chapter 3. Performance is ranked from 1 (best) to 3 (worst) performance. Highlighting reveals significant comparisons: gold = best/tied for best; silver = second best/tied for second best; bronze = worst performance. Cells without highlighting reflects no significant differences. T = Typing, V = Visual, W = Writing. Novel Font = letter recognition task with novel fonts. Writing = writing letters to dictation. Spelling = spelling words to dictation. Reading = word reading. Length Effect = effect of word length on word reading accuracy.

Trajectory of Learning	T	V	W
Time to Criteria	2	3	1
Recognition: Rate of Acc. Improvement	1	3	2
Recognition: Rate of RT Improvement	1	2	3
Recognition: Post-test Acc.	2	3	1
Recognition: Post-test RT	3	2	1

Generalization	T	V	W
Novel Font Acc.	3	2	1
Novel Font RT	3	2	1
Writing	2	3	1
Spelling	3	2	1
Naming Acc.	2	3	1
Naming RT	3	2	1
Reading Acc.	3	2	1
Reading Length Effect	3	2	1

Retention	T	V	W
Recognition Acc.	2	3	1
Recognition RT	3	2	1
Writing	2	3	1
Naming Acc.	2	3	1
Naming RT	3	2	1

CHAPTER 5 – GENERAL DISCUSSION

The Writing Condition resulted in consistently superior behavioral performance, in particular on measures of generalization (see Table 5-1). The Writing Condition was significantly better than both the Typing and Visual Conditions on the following tasks: Letter Recognition (RT), Novel Font Letter Recognition (RT), Writing Letters to Dictation, and Letter Naming (accuracy, post-training time point, and RT, follow-up time point). The Writing Condition was also significantly better than the Typing Condition on the Spelling Words to Dictation task, and in terms of the effect of length on the Reading Words task. The Writing Condition resulted in the best performance, numerically, on nearly every measure. How did this happen? In Chapter 1, five possible sources of such benefits were discussed, which would indicate that the effect of writing experience stemmed from incidental factors: (1) variable visual input, (2) an effort account, (3) selective rehearsal displacement, (4) transfer-appropriate processing, and (5) distinctiveness processing. The first three of these were addressed through the experimental design of the training study, and are not supported by the results reported here. The transfer-appropriate processing account is challenged to explain why the Writing Condition excelled even on the Letter Naming task, given that the writing training task does not more readily transfer to the task demands of letter naming (as opposed to, say, the Writing Letters to Dictation task). This leaves only the distinctiveness processing theory, which remains a viable possibility—as such, this theory is returned to in the final account presented below. Below, the performance of the three learning Conditions on the assessment tasks is reviewed to facilitate discussion of this account.

1. The Typing Condition

The Typing Condition presented a challenging learning task (see Appendix C) that did not well support generalization to other tasks. Participants in the Typing Condition struggled on tasks that required knowledge of the letter sounds in particular, such as Spelling to Dictation, Letter Naming, and Reading Words, and in general they were slow at visually processing the letters. Importantly, the Typing Condition was found to be the only group that failed to show any evidence of SLI effects, either on behavior in the Same/Different Judgment task, or in the RSA of the fMRI data (see section II of this chapter). This is consistent with the theory that symbolic letter identity (SLI) plays a key role in mediating between the multiple representations of letters. Instead of developing a robust amodal, symbolic letter representation, the Typing Condition resulted in narrower visual representations (e.g., font-specific) and facilitated learning of only very specific processes—namely, those needed to perform a visual search to find the correct key on the keyboard. They were also seen to be more heavily influenced by the letter names (in both the Same/Different Judgment task and the RSA results), which is suggestive of the possibility that letter names may be used to transcode between different modality-specific representations prior to learning SLIs.

2. The Visual Condition

The Visual Condition presented participants with the least engaging, easiest training task (see Appendix C). This may have led to slower progress in reaching criteria, but allowed the participants to attend to information presented in the training videos that participants in the Typing Condition may have been too busy for: the letter names, sounds, and the *dynamic* visual features portrayed through the letter animations. The claim that the Visual Condition resulted in relatively good learning of letter sound information is substantiated by their performance on the Spelling Words to Dictation and Reading Words tasks, the only two tasks which required letter sound knowledge, and on which they outperformed the Typing Condition and were not significantly different from the Writing Condition. The case for the visual condition having learned the dynamic visual information is best supported by the RSA results (see section II of this chapter).

3. The Writing Condition

Finally, the Writing Condition was the most beneficial method for learning letters. There were no important measures on which the participants in the Writing Condition did not perform best, a fact that is even more striking when considering that those superior results were obtained after *fewer* total training sessions (3.7 sessions versus 3.9 and 4.3 for typing and visual study, respectively). A specific result from the Writing Letters to Dictation task was that writing experience may specifically help with "breaking" mirror invariance (Pegado, Nakamura, & Hannagan, 2014), whereas even intense visual study is insufficient to do so. But the benefits of writing experience extended well beyond the ability to write letters, and went beyond visual recognition tasks. The evidence resulting from this investigation is that learning SLI representations was facilitated the most by writing training, and this supports the conclusion that these representations allow for faster and more reliable mapping between different letter representations (e.g., from letter-shapes to names or sounds and *vice versa*). A major piece of evidence that writing experience supported learning

SLIs is provided by the Same/Different Judgment task, where writing training resulted in a significantly larger effect compared to the Typing and Visual conditions, such that RT was slower to pairs of letters sharing SLI than to all other pairs. Converging evidence came from the RSA results (discussed in the next section).

A Final Account

SLIs are proposed to have a critical role of mediating between different letter representations, necessary for performing any task that requires outputting letters in one representational format given input in another. This abstractionist framework is depicted in Figure 5-1. I propose that the writing training task in particular facilitated development of SLI representations, because it provided the most experience with mapping between different modality-specific letter representations. This was the case because the requirement of the writing task itself, coupled with the requirement of reaching criteria on the letter recognition task, encouraged learning to map between visual, motoric, and phonological representations. Although it is of course possible to copy the letter-shapes without a stored motor plan, repetition of the act of writing clearly resulted in learning and storage of motoric representations. In the Typing Condition, repetition of the act of typing could also result in a stored spatial representation of the letter locations on the keyboard, however the results were clear that whatever memories of these locations developed, they were not robust (RT during the typing task remained very slow; see Appendix C). This account does predict that, given sufficient time, typing training might also result in SLI representations, but would not be expected to do so until the participants attained the ability to touch-type (i.e., typing without performing a visual search for the keys).

However, the non-arbitrary relationship between visual representations and motoric representations may also be crucial, and by comparison the arbitrariness of the keyboard layout may prevent typing training from ever being as effective as writing training. This is also suggested by distinctiveness processing theory, which proposes that the "production effect" (MacLeod et al., 2010) will only be effective for promoting recall and recognition if the responses that are produced during study are distinctive. That is, the responses must differentiate between the studied items—it is thus not clear that one key press compared to another would be sufficiently distinctive. As for the Visual Condition, no requirement of the visual probe/target task necessitated any transcoding at all (beyond associating the visual and auditory inputs together), given that it was an entirely visual task, and thus SLI representations would not obviously be developed or strengthened by that training.

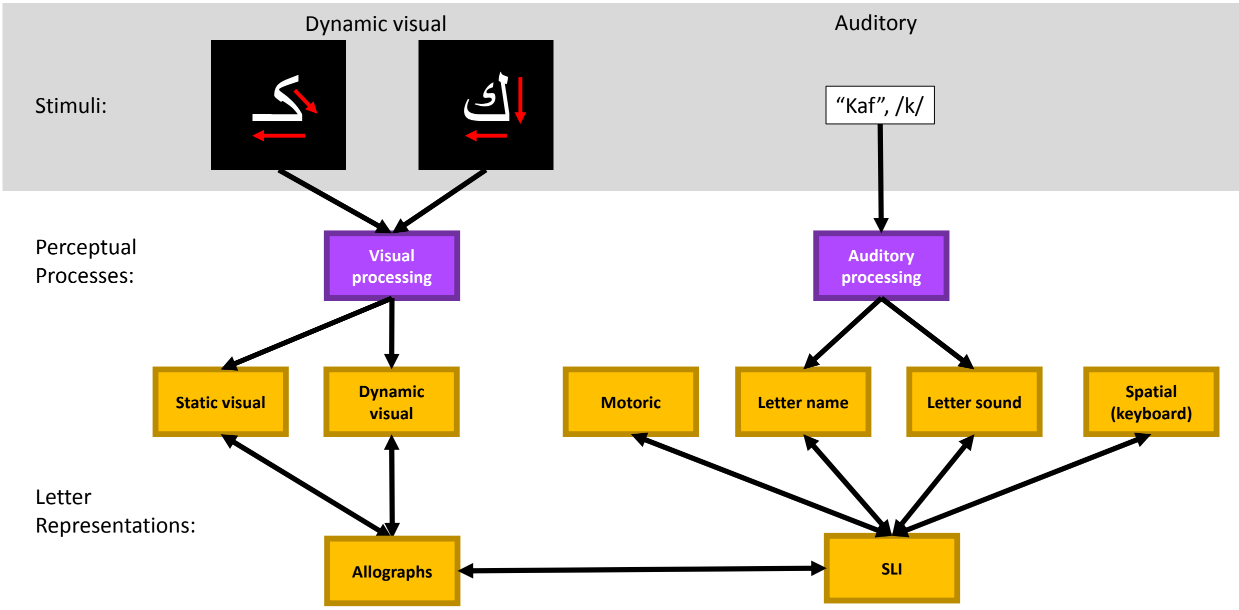

Figure 5-1. An abstractionist framework of the letter representations and processes during the training tasks. The stimuli reflect the animated letters shown to participants in all conditions with the accompanying audio. Mapping between visual, phonological, motoric, and spatial (i.e., keyboard location) representations requires mediation through SLI, given the arbitrary relationships between those modalities.

The effects of writing experience in this study are similar to what has been termed the "drawing effect" (Wammes, Meade, & Fernandes., 2016). In the study of Wammes and colleagues (2016), it was found that words were better memorized if participants were asked to draw pictures of them. It was argued that the benefit of drawing was that it combined elements of both generation and production—the participants must themselves generate semantic features of the words, the associated visual features, the motor plans to draw these features, and then of course they must also produce them. Moreover, the authors put forth what they called a "synergistic interaction" (Wammes, Meade & Fernandes, 2016, 1771) to explain the fact that the total benefit of drawing was greater than the sum of the benefits obtained by other learning conditions. Specifically, they also had participants memorize the words in three other conditions: by only listing visual features of the target words, by visualizing them through mental imagery, or by viewing pictures of them. The performance of those in the drawing condition was higher than what would be predicted if it were a linear combination of the effects of the other three conditions. The drawing effect is similar to the SLI account here, in that the multiple representations of letters were engaged by a writing task that entailed multiple ways of both generating and producing features of letters. What the SLI account *additionally* proposes is that, at least in the case of letters, the interaction between the processes and representations for generating and producing these different features is mediated by an amodal representation, SLI.

This account must also explain why the Visual Condition outperformed the Typing Condition, given that the visual training task is not predicted to especially support learning SLI representations. The explanation lies in the performance of the participants trained in the Visual Condition on tasks involving the letter sounds. The letter sound information was never necessary during training, but was tested only at post-training in the Spelling Words to Dictation and Reading Words tasks. One argument is that the relatively poor performance of the Typing Condition on these tasks was evidence that the difficulty of the typing task affected learning the letter sounds, which were presented after the letter animation and letter name[16]. Anecdotally, participants in the Visual Condition tended more often to covertly repeat the letter name and sound, which is perhaps not surprising given that their training

[16] The letter animations took place over 1000ms, whereas the audio of the letter name and sound required 2000ms. Thus, depending on the length of the letter name, the audio of the letter sound tended to play after the animation was completed (i.e., coincided with the static image), whereas the audio of the letter name coincided with the dynamic image.

task could be performed only after this information was presented, and so they were free to focus on this information. This differed from the Typing and Writing conditions, where it was possible to begin performing the training task while the auditory information was still being presented. In short, the Visual Condition clearly resulted in learning the letter names and sounds nearly as well as did the Writing Condition. Because associating letter names, sounds, and shapes is achieved via SLI in this abstractionist account, the Visual Condition thereby had a stronger SLI representation relative to the Typing Condition, where less learning of the letter names and sounds was achieved. The Writing Condition, on the other hand, clearly learned not only how to map between phonological and visual representations, but also between phonological and motoric, and visual and motoric, representations, further strengthening the SLI representation.

Challenging the Embodied Account

A possible embodied cognition framework is presented in Figure 5-2, depicting an alternative architecture for transcoding between letter representations by direct connections between modality-specific contents, instead of an amodal SLI representation. In the architecture depicted in that figure, associations between the letter names and information in other modalities is proposed to allow retrieving one type of information from another. However, the evidence found in this dissertation did not support a critical role for letter names during letter perception, and indeed primary auditory cortex has not been consistently activated during letter processing tasks in the same way as have parts of somatosensory and motor cortices. Of course, embodied cognition views are not limited to proposing that letter names facilitate letter processing, and can posit as many direct across-modality connections as needed. However, critically, no *amodal* representation ever needs enter into such a framework, and as such the positive findings of SLI here are a direct challenge to embodiment. While it is only embodiment theories that reduce concepts to sensory/motor representations, grounded cognition theories more generally are skeptical that amodal representations exist. Grounded cognition views then must either accept that SLI represents an instance of an abstract amodal concept, or else that the SLI representation is not in fact amodal but rather multimodal/supramodal. As outlined in Chapter 1, current proposals for how abstract concepts (such as letter identity) can be represented without amodal representations include multimodal or "supramodal" representations, distilled abstraction, and distributed linguistic representations (for a review see Barsalou, 2016).

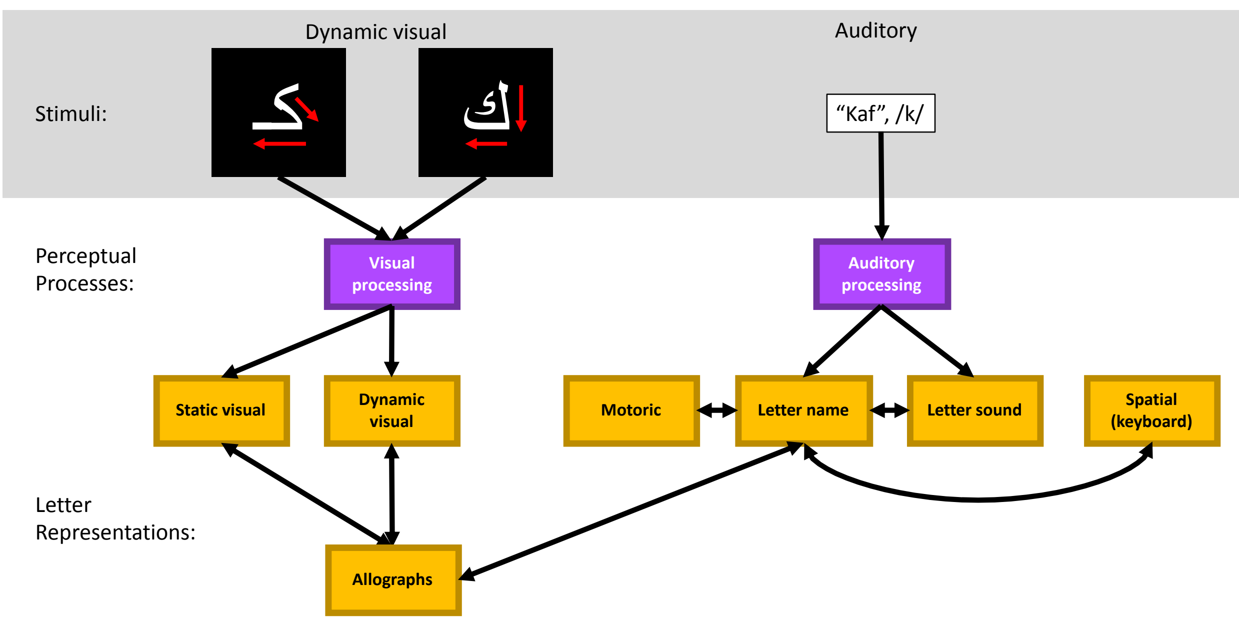

Figure 5-2. A possible embodied cognition framework of the letter representations and processes during the training tasks. The stimuli reflect the animated letters shown to participants in all conditions with the accompanying audio. Mapping between visual, phonological, motoric, and spatial (i.e., keyboard location) representations is mediated by

direct modality-specific connections, in this example, through association of different modality information with letter names.

The evidence in this dissertation argues against the possibility that the SLI representation is only multimodal, however. This is because the SLI representation accounted for *unique* variance in simultaneous regression (in both the Same/Different Judgment and the RSA results)—in other words, letters were perceived as more similar to one another if they shared the same identity, even when controlling for their shared representations along modality-specific dimensions. This suggests at the very least that processes like "multimodal compression" or "distilled abstraction" (see Introduction), which have been proposed by grounded cognition theorists, (Barsalou, 2016; Binder, 2016; Jamrozik, McQuire, Cardillo, & Chatterjee, 2016; Martin, 2016) would need to result in representations that are so abstract as to no longer be tied to any of the modalities from which they arose. This point is returned to in section II ("Multimodal and Amodal Letter Representations").

In summary, the abstractionist account I propose here claims that writing experience does benefit letter learning, and does so in particular by strengthening the ability to map between different letter representations via amodal SLI representations. The next section discusses the broader implications of this account to the grounded/abstractionist cognition theories, beyond the domain of letter processing.

II. Multimodal and Amodal Letter Representations

In this section, I review two pieces of evidence that are consistent with grounded cognition theory, broadly construed. I then present two challenges to these views that instead support abstractionist positions. First, regions that have been previously described as part of the "visual-motor letter-processing" network (James, 2017) were identified within the Letter Learning Network (described in Chapter 4), replicating the finding that this network is activated during simple observation of single letters (in this case, a symbol detection task). The first novel, and critical, result reported here was that many of the clusters of activity were found to include sensory/motor representations: low and higher level visual representations, motoric representations, and phonological representations. These were found outside of primary somatosensory and primary motor areas, and therefore substantiate the first claim of grounded cognition, that activation in these regions at least includes sensory/motor representations. Most importantly, motoric representations (not just visual ones) were identified even though the scanner task did not involve motor production of letter shapes.

The second finding supporting a grounded cognition position is that associations were found between sensory/motor representations and behavioral performance on letter processing tasks. The most widespread type of representation across the brain actually was motoric. However, many of the clusters that seemed to reflect motoric representations in fact may be better understood as reflecting the representation of the dynamic visual features. This interpretation was supported by the fact that roughly two-thirds of the motoric representation clusters overlapped with those representing visual information (pixel overlap and/or shared visual features; see Chapter 4). Indeed, the motoric representation clusters associated with the Writing Condition, and/or with behavioral performance on the Writing Letters to Dictation task, stood out from the clusters associated with the Typing and Visual Conditions and/or the behavioral tasks that did not require writing: the writing-associated clusters almost exclusively represented *only* motoric information, whereas the visual- and typing-associated clusters by and large simultaneously represented visual information (as established by the multiple regression LMEM). This suggested that those latter clusters actually reflected visual dynamic, not motoric, information.

Overall, the results strongly indicate that sensory/motor activity is *not* epiphenomenal, in particular the results showing associations between motoric/visual-dynamic representations and letter recognition, naming, and word reading abilities. However, the other major findings from the RSA results were highly problematic for any grounded cognition view that predicts letter processing can be achieved without amodal representations, including embodied theory. First, clusters of activity were found that reflected amodal SLI representations, and SLI was also seen to influence behavioral Same/Different Judgments. Second, strong SLI evidence was found only for those with writing experience, and importantly, these representations was also associated with faster letter recognition.

Therefore, despite the apparent role of sensory/motor representations, and some evidence that writing experience uniquely produces motoric representations that in turn support letter perception, a core tenet of grounded cognition is called into question. The results here present a challenge to most of the grounded cognition hypotheses, including the theory of "neural reuse" (Anderson, 2010; Barsalou, 2016; Martin, 2016). As described by Martin, the neural reuse theory is that "representations are grounded by virtue of their being situated within (i.e., partially overlapping with) the neural system that supports perceiving and interacting with our external and internal environments." (980, Martin, 2016). While the locations of the letter representations reported here are consistent with this claim, their content is not. Specifically, the amodal SLI representation counters the neural reuse theory. Succinctly worded by Barsalou, "if the neural reuse hypothesis is correct, it follows that when a conceptual process utilizes the resources of a modality-specific processing stream, the resultant conceptual representations have a modality-specific character, not an amodal one" (page 1131, Barsalou, 2016). This is taken to be so because the processes and representations that initially develop in these areas are proposed to necessarily be modality-specific, and as such the neural activity is constrained to reflect content that is tied to the modalities, rather than abstract amodal content. Amodal representations, if they exist, should not be found in the same substrates as sensory/motor representations.

The SLI representation reported here is potentially consistent with the proposal of Binder (Binder, 2016), which is that abstract concepts are instantiated in the brain not through amodal symbols, but rather through "convergences of information at crossmodal levels" (page 1103, Binder, 2016) that lead to what is termed "cross-modal conjunctive representations" (CCRs). As such, the resultant representations are best not thought of as amodal. However, there is an interpretation of the results of this dissertation that is consistent with this theory, if granted that "in the limit… CCRs can become so abstract as to sometimes become amodal symbols" (page 1132, Barsalou, 2016). For example, consider the L precentral gyrus cluster, where the simultaneous LMEM regression found evidence of visual, motoric, and SLI representations in heavily overlapping areas. This finding is certainly consistent with the proposed CCRs, allowing that the representation indeed has become so abstract as to be amodal. In addition to this, another argument in favor of Binder's proposal is that the clusters that reflected more than one information type, including the L precentral gyrus cluster showing SLI representation, were nearly all found within the areas (see Appendix A) identified as part of a "supramodal 'conceptual hub'" (Binder, 2016; Binder, Desai, Graves, & Conant, 2009), including inferior parietal cortex, ventromedial temporal cortex, dorsomedial prefrontal cortex, ventromedial prefrontal cortex, inferior frontal gyrus, and precuneus.

Taken together, these results reveal that amodal representations do exist. The evidence is consistent with the possibility that they may arise (i.e., that they are learned) from conjunctions of different modality-specific information—however, the resulting representations seem to no longer depend on modality-specifeic information that may have been needed during the learning stages.

Do Amodal Representations Stand Alone?

One outstanding issue in the grounded-abstract cognition debate relates to the status of amodal representations (allowing that amodal representations do exist). The strongest abstractionist claims are that amodal, symbolic concepts can operate in a stand-alone manner, without any concomitant processing of modality-specific representations (Barsalou, 2016; Leshinskaya & Caramazza, 2016; Mahon, 2015; Mahon & Caramazza, 2008; Mahon & Hickok, 2016). The argument *against* amodal representations has been that without any modality-specific content whatsoever, such representations remain ungrounded and are therefore meaningless—hence the complaint of grounded theorists that amodal symbols would serve no *purpose,* if instead modality-specific representations would serve.

I argue that at least one of the purposes of amodal representation is exactly to allow for concepts that do *not* rely on modality information. This is deeply important because otherwise, the loss of any modality-specific content will result in a fundamentally different concept. While it is certainly not inconceivable that this would be true, empirical results suggest otherwise. For example, extensive evidence shows that concepts of both objects and events are not fundamentally different among the congenitally blind (Bedny, Caramazza, Grossman, Pascual-Leone, & Saxe, 2008; Bedny, Pascual-Leone, Dodell-Feder, Fedorenko, & Saxe, 2011; Bedny, Pascual-Leone, & Saxe, 2009). There is even stronger evidence from neuropsychology (see e.g., Mahon & Caramazza, 2008) that loss of one modality post-stroke does not lead to altered conceptual processing. I thus propose an extension of abstractionist theory: *learning* abstract, amodal concepts likely depends on sensory/motor representations, although no specific modalities are required. However, once learned, amodal representations serve to support stable concepts that no longer require accessing the sensory/motor representations that were part of the learning process. This generates testable predictions, which are discussed in the final section below.

III. Implications & Future Directions

This dissertation makes two major claims, the first about the role of writing experience in letter learning specifically, and the second about the how amodal representations arise from sensory/motor processes. The first has educational implications, as understanding whether and why certain learning experiences are beneficial can inform best practices in education. Based on the evidence from this investigation, I propose that the reason writing experience matters for learning letters is that it strengthens amodal SLI representations, which are used for mapping between different letter representations. This predicts that any learning condition that provides additional experience with transcoding between multiple letter representations will facilitate learning SLIs, and thereby provide benefits similar to what is seen with writing training. This does suggest that it is not motor learning *per se* that is important for letter learning, but nonetheless writing would seem to be the most natural way of learning letters (not to mention it is a useful skill in itself). For example, more extensive typing training, such that participants become able to touch-type, would be predicted to also result in SLI representations. Memorizing a keyboard layout, however, seems to be more challenging than memorizing how to write a shape. This is undoubtedly due at least partially to the fact that letter-shapes and motoric representations are related, whereas keyboard layouts are arbitrary. Alternatively, and simpler than an extended typing training condition, would be a condition that emphasizes learning to name the letter/produce their sounds. Such a condition should similarly facilitate developing SLI, although there again the relationship between letter-shapes and names/sounds is arbitrary and may be less beneficial than writing practice.

One result that has perhaps been de-emphasized in the discussion thus far is that the Visual Condition in fact resulted in nearly equal performance to the Writing Condition on several tasks, including the Spelling Words to Dictation and Reading Words tasks. Given that the ultimate goal of written language instruction is to teach students how to spell and read, it seems important that such good results were achieved without writing experience. While certainly the Writing Condition was the best, the suggestion is that the visual training task still enabled good learning. This was surely due in part to the efforts taken to equate the three learning Conditions, in particular by affording even the Visual Condition participants with exposure to variable font input (Li & James, 2016), but also the novel adoption of dynamic videos for the purposes of training. In fact, the results were highly suggestive that the dynamic visual information portrayed by these videos was crucial for learning the letters. Perhaps a more challenging visual task, such as requiring participants to perform a probe/target task where the distractors are similar letter shapes (as opposed to non-alphanumeric symbols, as was done here) would lead to even better performance. Another interesting possibility raised by the results, in conjunction with the literature on the production effect, is that requiring participants to simultaneously produce the letter in multiple modalities (e.g., both write the letter *and* say its name) is likely to produce even stronger results. This would be consistent with the findings of the "drawing effect" (Wammes, Meade, & Fernandes, 2016), and is also predicted, by the abstractionist framework presented here, to facilitate learning amodal SLI representations even further.

The second major claim in this dissertation is that the evidence for amodal SLI representations contributes to the conclusion that cognition does not reduce to sensory/motor representations. While this goes against embodied cognition, it does not necessarily run counter to all groundedness claims. For example, the claim is potentially consistent with the "crossmodal conjunctive representation" account of Binder (Binder, 2016), if taken to the limit that initially multimodal representations become amodal, after learning results in a high degree of abstraction. Future work might further examine the claim that these representations are truly amodal, and that they do not ultimately depend on any specific modalities to learn—for example, participants could be trained to write letters in two groups, differing according to what motor plans they were taught. These motor plans could be manipulated by changing the direction and order of strokes (similar to Babcock & Freyd, 1988), such that the predicted similarity of the letters would differ greatly depending on which motor plans were learned. Under such conditions, it would be predicted that an RSA-LMEM analysis would find interactions between these two groups of participants in terms of their motoric representations, but *not* their SLI representations.

It was also suggested that motoric representations may in part be useful for letter recognition because of the relationship between how letters are written and the resulting visual shapes. This might predict that during auditory letter processing (e.g., of letter names), motoric representations would not be so extensively activated as they were found to be during visual letter processing. This could be tested by essentially the same procedures used in this dissertation, but by contrasting RSA results from data acquired during blocks of visual letter presentations (as in the Symbol Detection Task used here) with blocks of auditory letter presentations.

This dissertation is the result of a research paradigm that was developed specifically to extensively integrate behavioral and neuroimaging techniques. The results of the RSA would not be nearly as informative about cognition were they not related to detailed information about what the participants knew about the letters, and how they came to know it. This information was only able to be collected because of the longitudinal and training aspects of the study. In fact, the behavioral and neuroimaging experiments were all designed from their inception by taking into account how they could be used *together* to strengthen the inferences that might be drawn from the results. Doing so provided an exponentially richer empirical basis from which to draw inferences.

One goal of this dissertation was to provide the basis for further research that has educational implications, and as such the research paradigm used here exemplifies a model of how experiments can be designed that both address fundamental cognitive science questions, and provide the basis for future translational research. Indeed, the results reported here do not represent the entire breadth of the data that was collected. For example, in addition to the RSA results of the post-training time point, data is also available from the pre-training time point. The participants also performed many of the same tasks, both behavioral and neuroimaging, with Roman letters (e.g., the Same/Different Judgment task, the Letter Naming task, and the Symbol Detection Task that is the basis of the RSA results). A number of measures of individual differences were also collected (e.g., measures of short term memory, visual working memory, verbal fluency). Thus, in addition to the future directions discussed above, this dissertation already provides more information that can be used to test questions about cognition other than the nature of conceptual representations.

IV. Conclusion

The findings of this dissertation further our understanding of the nature of conceptual representations in the mind/brain, and have bearing on the debate between grounded and abstract theories of cognition. I conclude that the evidence presented here supports the view that cognition involves both groundedness and abstraction. Sensory/motor representations were found to be recruited for letter perception, and moreover were associated with behavioral performance on letter processing tasks. This argues against a strong abstractionist claim that sensory/motor activity may be epiphenomenal. However, symbolic letter identities (SLI), an amodal representation, were also associated with behavioral performance, and were strongest in the Writing Condition. These results challenge grounded theories that reduce concepts to sensory/motor representations, and support the existence of conceptual representations that are truly amodal. On the basis of these findings, I propose that writing experience is particularly beneficial to learning letters because it strengthens connections between various modality-specific letter representations, mediated by amodal SLI representations.

Appendices

Appendix A – Full RSA Results

This appendix reports the full results of the RSA analyses, both the Learning Experience Analyses and the Behavioral Measure Analyses. This mirrors the results reported in Chapter 4, but additionally includes the between-Condition comparisons (e.g., Typing versus Writing, Visual versus Writing, etc.) and the main effects (i.e., representations found when collapsing across the three learning Conditions).

Key: T = Typing, V = Visual, W = Writing; ME = Main Effect
TvV = Typing versus Visual, TvW = Typing versus Writing, VvW = Visual versus Writing
Recognition = Letter Recognition RT
Naming = Letter Naming RT
Writing = Writing Letters to Dictation Accuracy
Reading = Reading Words accuracy

1. Low Level Visual Representation (Pixel Overlap)

Table A-1. Clusters associated with low-level visual representations (pixel overlap). Left panel: positive associations. Right panel: negative associations. Cerb = cerebellum, IPL = inferior parietal lobule, PCC = posterior cingulate cortex, FG = fusiform gyrus, IFG = inferior frontal gyrus, dPMC = dorsal premotor cortex, PostCG = postcentral gyrus, STG = superior temporal gyrus.

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
ME	25	-59	-26	-4.11	15	R cerb
ME	-48	-39	44	-3.9	11	L IPL
T	-41	-66	-33	-4.34	33	L cerb
T	0	-39	21	-4.58	14	bilateral PCC
T	42	-78	-17	-3.67	20	R post FG
V	-48	10	2	-4.42	16	L IFG operculum
TvW	-39	-61	-32	4.57	15	L Cerb
Naming	-41	16	2	4.61	20	L IFG operculum

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
Recognition	26	5	48	-5.27	35	R dPMC
Writing	42	4	52	3.92	12	R dPMC
Reading	4	-71	10	4.22	24	R calcarine sulcus
Reading	-68	-20	22	4.36	16	L PostCG
Reading	-56	9	-3	4.52	16	L STG
Reading	46	-62	-21	3.86	20	R middle FG

2. Higher Level Visual Representation (Visual Features)

Table A-2. Clusters associated with higher-level visual representations (visual features). Left panel: main effects and learning condition-specific effects. Right panel: interactions between learning experiences, and with behavioral tasks. PreCG = precentral gyrus, IFG = inferior frontal gyrus, ITG = inferior temporal gyrus, MFG6 = middle frontal gyrus Brodmann Area 6, SMG = supramarginal gyrus, SPL = superior parietal lobule, DLPFC = dorsolateral prefrontal cortex, VLPFC = ventrolateral prefrontal cortex, LOS = lateral occipital sulcus.

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
ME	-57	8	7	4.32	12	L PreCG
ME	-42	-84	-13	4.45	20	L posterior fusiform
V	-53	-75	-3	3.64	14	L V5/MT
V	-53	13	6	5.42	26	L IFG operculum
V	-47	-68	-8	4.96	62	L middle & posterior fusiform, L ITG
V	-44	-6	39	3.58	13	L MFG6
V	-43	-52	51	5.25	39	L SMG
V	46	-69	-2	4.59	34	R middle fusiform
W	-57	-7	7	4.24	11	L PreCG
W	-50	8	17	5.225	14	L PrecG (superior)
W	-29	-67	46	4.26	12	L SPL

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
Naming	-55	11	14	-4.03	19	L PreCG, L PrecG (superior)
Naming	-44	18	-1	-4.58	28	L IFG operculum
Reading	-48	-42	55	5.56	64	L SMG
Reading	-48	25	23	4.25	15	L DLPFC
Reading	-48	25	23	4.25	15	L DLPFC
Reading	-44	6	25	4.68	21	L PrecG (superior)
Reading	-14	-67	38	5.21	30	L precuneus
Recognition	-53	-71	-2	-3.86	10	L V5/MT
Recognition	-53	4	11	-3.82	16	L PreCG
Recognition	-50	10	25	-4.19	28	L PrecG (superior)
Recognition	-41	-81	-13	-5.21	27	L posterior fusiform
Recognition	-36	25	22	-3.82	19	L DLPFC
Recognition	-11	-69	38	-3.4	15	L precuneus
Recognition	41	40	7	-4.78	13	R VLPFC
Recognition	43	-93	2	-4.23	9	R LOS
TvV	-47	-50	55	4.44	28	L SMG
TvV	-39	-81	-11	4.53	29	L posterior fusiform
TvV	-14	-66	43	3.98	13	L precuneus
TvV	42	-63	-14	4.48	11	R middle fusiform
TvW	-54	14	16	3.82	17	L PrecG (superior)
VvW	-47	10	6	-3.9	13	L IFG operculum
VvW	-41	-81	-14	4.53	39	L posterior fusiform, L ITG
VvW	-28	-64	44	3.97	14	L SPL

3. Motoric Representation (Motor Bistrokes)

Table A-3. Clusters positively associated with motoric representations (motor features). Left panel: main effects and learning condition-specific effects. Right panel: positive interactions between learning experiences, and with behavioral tasks. PreCG = precentral gyrus, STG = superior temporal gyrus, cerb = cerebellum, FG = fusiform gyrus, SMG = supramarginal gyrus, FEF = frontal eye fields, meSFG = medial superior frontal gyrus, SPL = superior parietal lobule, IPS = intraparietal sulcus, DLPFC = dorsolateral prefrontal cortex, ACC = anterior cingulate cortex, IFG = inferior frontal gyrus, MFG6 = middle frontal gyrus (Brodmann Area 6).

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
ME	-56	8	16	-5.44	43	L preCG (sup.)
ME	-54	9	-5	-4.42	13	L STG
ME	18	-72	-28	-5.43	18	R cerb (post. inf.)
ME	33	-73	-20	-3.79	11	R cerb (post.)
ME	39	-73	-24	-4.16	12	R post. FG
T	-51	-75	2	-4.41	25	L V5/MT
T	42	-67	-5	-3.91	13	R V5/MT
TvV	-47	-47	58	-5.662083	41	L SMG
TvV	-38	-84	-13	-4.41	15	L post. FG
TvV	-37	3	26	-3.962824	11	L FEF
TvV	-14	-69	40	-4.862972	28	L precuneus
TvV	1	25	52	-4.752724	15	bilateral meSFG
TvV	13	-65	40	-4.913815	18	R precuneus
TvV	37	-69	40	-4.458631	17	R SPL
TvW	-23	-76	39	-5.83	66	L post. IPS
V	-48	34	32	-4.801017	16	L DLPFC
V	-46	-67	-6	-4.43	10	L ITG
V	-44	-48	55	-6.420595	83	L SMG
V	-44	22	26	-5.988792	142	L IFG, L PreCG, PreCG (sup.), L DLPFC
V	-41	-67	-14	-4.33	18	L mid FG
V	-38	-85	-12	-4.06	12	L post. FG
V	-32	0	33	-6.546516	61	L FEF
V	-15	-68	39	-5.868388	25	L precuneus
V	-11	-18	36	-5.465593	12	L cingulate sulcus
V	-8	11	24	-5.19948	20	L ACC
V	-3	30	40	-5.362441	87	bilateral meSFG
V	-3	37	35	-4.314883	14	L anterior meSFG
V	12	-64	40	-4.723657	32	R precuneus
V	21	-72	-31	-6.673416	26	R cerb (post. inf.)
VvW	-51	-68	-20	4.49	9	L mid FG (lateral)
VvW	-49	13	8	4.672048	18	L IFG operculum
VvW	-47	34	31	5.317067	16	L DLPFC
VvW	-44	-52	52	6.029407	47	L SMG
VvW	-38	-84	-14	-3.57	14	L post. FG
VvW	-37	-71	-12	-4.44	10	L mid FG
VvW	-36	4	41	4.075641	18	L FEF
VvW	-24	-78	44	-4.691848	23	L post. IPS
VvW	-14	-68	39	4.583352	18	L precuneus
VvW	1	25	46	5.166742	33	bilateral meSFG
VvW	14	-67	41	3.992679	14	R precuneus
VvW	49	-72	-17	4.09	21	R mid FG
W	-34	-93	-1	-3.86	14	L LOS
W	-23	-79	39	-5.21	43	L post. IPS
W	33	-65	-26	-4.59	12	R cerb (post.)
W	48	-71	-17	-5.16	31	R post. FG
W	49	-63	-10	-4.86	13	R mid FG

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
Naming	-56	13	-9	5.303112	15	L STG
Naming	-54	10	15	4.40964	25	L preCG (sup.)
Naming	-47	14	7	4.919203	29	L IFG operculum
Naming	-39	25	22	4.148455	13	L DLPFC
Naming	-11	-68	37	5.038149	29	L precuneus
Naming	13	-73	43	3.790202	23	R precuneus
Reading	-46	-47	55	-7.714195	76	L SMG
Reading	-45	-53	-11	-3.81	16	L anterior FG
Reading	-43	-78	-19	-3.69	12	L post. FG
Reading	-41	-70	-5	-3.49	9	L mid FG
Reading	-41	7	35	-4.413876	51	L preCG (sup.), L FEF
Reading	-9	-65	38	-6.539762	37	L precuneus
Reading	1	34	32	-4.621985	38	bilateral meSFG
Reading	13	-67	38	-4.360747	21	R precuneus
Reading	42	-65	-13	-3.91	10	R mid FG
Recognition	-63	-20	24	3.945317	13	L post.CG
Recognition	-41	14	-3	4.407196	12	L IFG operculum
Recognition	-39	-84	-14	5.2	63	L anterior, mid & post. FG, L ITG
Recognition	-23	-76	37	4.667494	12	L post. IPS
Recognition	-9	-65	37	5.445757	25	L precuneus
Recognition	-5	20	43	4.275994	38	bilateral meSFG
Recognition	3	-39	26	5.336084	19	bilateral PCC
Recognition	28	13	45	5.060601	22	R MFG6
Writing	-48	12	16	-4.5	20	L preCG (sup.)
Writing	-39	-56	-9	-4.14	27	L anterior FG

Table A-4. Clusters negatively associated with motoric representations. IPS = intraparietal sulcus, IPL = inferior parietal lobule, DLPFC = dorsolateral prefrontal cortex, VLPFC = ventrolateral prefrontal cortex. ME = main effect, T = Typing, V = Visual, W = Writing.

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
Recognition	42	-68	-5	-4.89	12	R V5/MT
Recognition	45	-50	43	-3.696916	11	R anterior IPS/R IPL
TvW	40	-41	44	5.29	20	R anterior IPS/R IPL
VvW	46	-32	43	4.981581	15	R anterior IPS/R IPL
W	36	-44	40	4.82	16	R anterior IPS/R IPL
Writing	40	31	23	5.01	25	R DLPFC
Writing	42	3	3	4.5	15	R VLPFC

4. Phonological Representation (Letter Names)

Table A-5. Cluster positively associated with letter name representations. STG = superior temporal gyrus. T = Typing.

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
T	-53	15	-3	-4.35	19	L STG

5. Amodal Representation: Symbolic Letter Identity (SLI)

Table A-6. Clusters associated with symbolic letter identity (SLI) representations. PreCG = precentral gyrus, SMA = supplementary motor area, LOS = lateral occipital sulcus. ME = main effect, T = Typing, V = Visual, W = Writing.

EFFECT	X	Y	Z	T-VALUE	voxels	AREA
Recognition	-50	10	12	3.28	11	L PreCG
TvW	-57	7	9	3.9	15	L PreCG
TvW	3	10	59	4.46	19	bilateral pre-SMA
VvW	1	11	59	4.22	18	bilateral pre-SMA
W	-57	7	9	3.9	14	L PreCG
W	1	12	61	3.49	16	bilateral pre-SMA
W	40	-85	2	3.86	9	R LOS

Appendix B – Negative versus Positive Associations in RSA Results

This appendix demonstrates an account of how negative associations (i.e., akin to anti-correlations) could arise in the RSA results, between observed patterns of neural similarity on the one hand, and predicted patterns of letter similarity on the other. Specifically, it was proposed in Chapter 4 that voxels responding selectively to a subset of features, in particular *distinctive* features, could result in negative correlations. It was discussed that the possibility of distinctive features are selectively attended to is not unfounded (Wiley & Rapp, under review; Fiset et al., 2008, 2009). A set of voxels that, given feedback from lower-level visual areas, responds to a subset of features could quite plausibly result in an apparently negative association between the neural similarity measure and the predicted measure, as follows.

As an illustration, consider the response of the following two hypothetical voxels to three different stimuli: Voxel A encodes information about the orientation of straight lines, and Voxel B encodes (binary) information about whether a shape is open or closed. Stimulus 1 has a single oriented line, Stimulus 2 has two oriented lines and closed space, and Stimulus 3 has no oriented lines but closed space. The predicted similarity of these three stimuli (using the procedure outlined in Chapter 3) would be 67% of features shared for the Pair 1-2, 0% for the Pair 1-3, and 67% for the Pair 2-3.

Despite the predicted high similarity of the Pair 1-2 (67%, the stimuli that share oriented lines) and the low similarity of the Pair 1-3 (0%), in Euclidean distance Stimulus 1 would be *more distant* from the other two, given simple assumptions. For example, if Voxel A encoded the stimuli respectively as 1, 2, and 0 (reflecting the number of oriented lines present in the stimuli), and Voxel B encoded the stimuli respectively as 0, 1, and 2 (treating closed space as a binary feature), then the relative distances of the stimuli would be that depicted (to scale) in Figure B-1. The correlation between the predicted similarity (0.67, 0, 0.67) and the neural similarity (1.0, 1.0, 0.6) would be *negative* (r = -0.5). The reason for this may be made more plain by interpreting Figure B-1 as representing the feature "oriented lines" on the x-dimension, and the feature "closed space" on the y-dimension: Stimuli 2 and 3 are thus equal on the y-dimension (both having closed space), whereas the three stimuli extend linearly along the x-dimension (due to have 0, 1, and 2 oriented lines). Depending on the relative weighting of the features, the predicted similarity can thus seem to be "inverted", i.e., anti-correlated, as in this example, where the Pair 2-3 is actually *less* similar than the Pair 1-2 (despite their predicted similarity of 67% versus 0%), because of the relative weighting of the feature dimension "oriented lines" compared to "closed space".

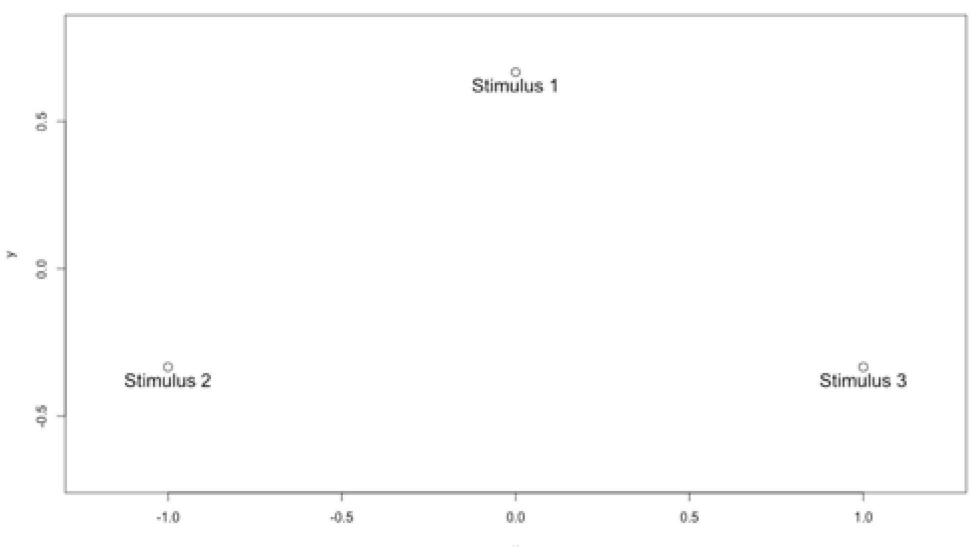

Figure B-1. Relative Euclidean distance in hypothetical neural space for three stimuli. Stimuli pair 1-2 is predicted to be equally similar as pair 2-3 (each sharing 2/3 of their visual features), but in the neural space pair 2-3 is actually more dissimilar. Likewise, the pair 1-3 is predicted to be *less* similar than the pair 1-2 (shared 0 features versus 2/3 features), but the relative distances are equal. The result is that the association between predicted similarity and observed similarity will be overall negative.

While conjectural in nature, the findings in Chapter 4 about the sign of the relationship between predicted and observe similarity suggest possible research directions. For example, careful manipulation of the visual features in stimuli might be used to both test the hypothesis, that RSA uncovers dimensions of featural representations, and furthermore to specifically determine what those features might be (a question that, at least in the case of letters, has eluded conclusive evidence).

Appendix C – Learning Condition: Training Task-Specific Results

The following tables and figures report the results from the specific training tasks used in the three learning Conditions: Typing, Visual, and Writing. Specifically, the Typing Condition task was to find the presented letter(s) on the keyboard and press them (in sequence, for word blocks). The Visual Condition task was a probe/target match decision (the probe was either the target Arabic letter presented on that trial, or a non-alphanumeric symbol). The Writing Condition task was to copy the letter-shape using pen and ink; only RT information is available for this condition.

Table C-1. RT to correct responses (top panel), and accuracy (bottom panel) for the learning Conditions' specific training tasks, across the (maximal) six sessions of training, during letter-blocks.

Letter-Blocks		Training Session					
Training Condition	RT (ms)	**1**	**2**	**3**	**4**	**5**	**6**
Typing	mean	3137	2813	2766	2780	2763	2824
	sd	*153*	*144*	*213*	*144*	*37*	*58*
Visual	mean	660	652	631	619	646	645
	sd	*46*	*79*	*69*	*65*	*59*	*47*
Writing	mean	2805	2747	2595	2642	2663	2390
	sd	*195*	*148*	*197*	*158*	*189*	*na*

Letter-Blocks		Training Session					
Training Condition	Accuracy	**1**	**2**	**3**	**4**	**5**	**6**
Typing	mean	62%	83%	89%	92%	90%	91%
	sd	*8%*	*9%*	*12%*	*7%*	*9%*	*6%*
Visual	mean	89%	87%	87%	92%	90%	90%
	sd	*6%*	*10%*	*13%*	*5%*	*5%*	*5%*

Table C-2. RT to correct responses (top panel), and accuracy (bottom panel) for the learning Conditions' specific training tasks, across the (maximal) six sessions of training, during word-blocks.

Word-Blocks		Training Session					
Training Condition	RT (ms)	**1**	**2**	**3**	**4**	**5**	**6**
Typing	mean	5731	5567	5589	5732	5739	5512
	sd	*411*	*441*	*391*	*513*	*29*	*180*
Visual	mean	672	670	666	637	683	663
	sd	*51*	*68*	*77*	*32*	*51*	*35*
Writing	mean	3356	3335	3276	3125	2941	3110
	sd	568	510	471	412	463	na

Word-Blocks		Training Session					
Training Condition	Accuracy	**1**	**2**	**3**	**4**	**5**	**6**
Typing	mean	52%	72%	78%	84%	85%	87%
	sd	*14%*	*19%*	*22%*	*17%*	*16%*	*12%*
Visual	mean	91%	89%	88%	93%	84%	85%
	sd	*7%*	*9%*	*11%*	*5%*	*6%*	*9%*

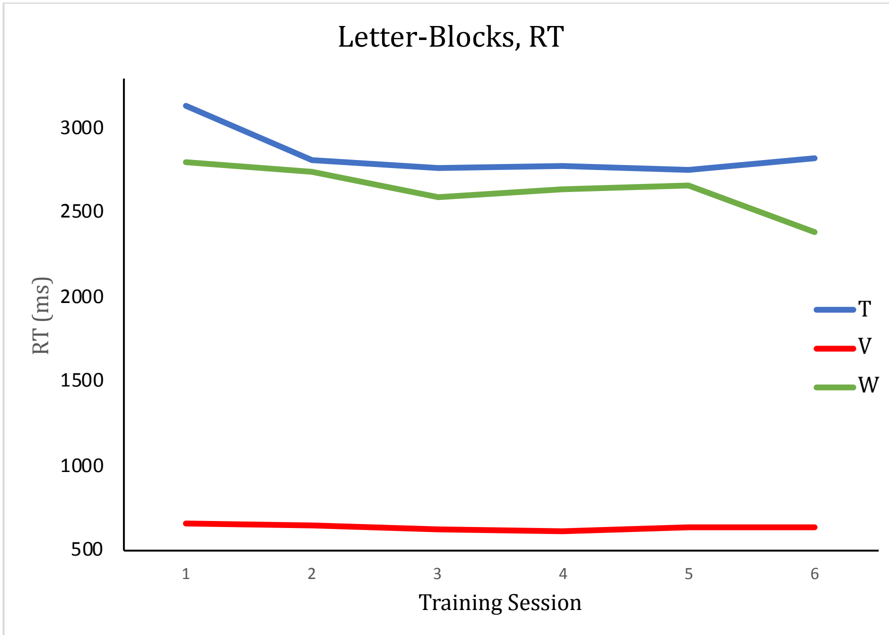

Figure C-1. RT to correct responses for the learning Conditions' specific training tasks, across the (maximal) six sessions of training, during letter-blocks. T = Typing, V = Visual, W = Writing.

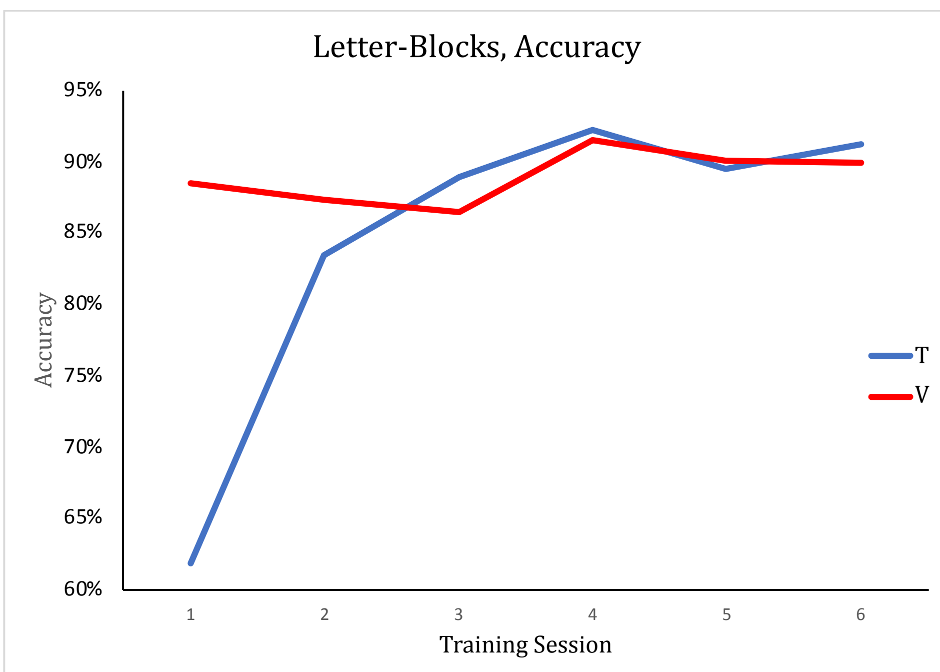

Figure C-2. Accuracy for the learning Conditions' specific training tasks, across the (maximal) six sessions of training, during letter-blocks. T = Typing, V = Visual.

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Curriculum Vitae

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