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## Handwriting generates variable visual input to facilitate symbol learning

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### Abstract

Recent research has demonstrated that handwriting practice facilitates letter categorization in young children. The present experiments investigated *why* handwriting practice facilitates visual categorization by comparing two hypotheses: That handwriting exerts its facilitative effect because of the visual-motor production of forms, resulting in a direct link between motor and perceptual systems, or because handwriting produces variable visual instances of a named category in the environment that then changes neural systems. We addressed these issues by measuring performance of 5 year-old children on a categorization task involving novel, Greek symbols across 6 different types of learning conditions: three involving visual-motor practice (copying typed symbols independently, tracing typed symbols, tracing handwritten symbols) and three involving visual-auditory practice (seeing and saying typed symbols of a single typed font, of variable typed fonts, and of handwritten examples). We could therefore compare visual-motor production with visual perception both of variable and similar forms. Comparisons across the six conditions (N=72) demonstrated that all conditions that involved studying highly variable instances of a symbol facilitated symbol categorization relative to conditions where similar instances of a symbol were learned, regardless of visual-motor production. Therefore, learning perceptually variable instances of a category enhanced performance, suggesting that handwriting facilitates symbol understanding by virtue of its environmental output: supporting the notion of developmental change through brain-body-environment interactions.

### Keywords

handwriting; development; categorization; embodiment; letters and symbols

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Among the reading readiness skills that are traditionally evaluated, the one that appears to be the strongest predictor of reading success is visual letter categorization (Scanlon & Vellutino, 1996; Snow, Burns, & Griffin, 1998). Therefore, improving letter categorization skills at an early age (pre-Kindergarten) is a crucial first step in improving overall literacy skills.

Although teaching children to categorize letters (instances of an ‘A’ belong to the named category ‘A’) is usually through sight and sound (seeing the letter, hearing its name, and hearing the sound it makes), growing research supports the idea that handwriting practice facilitates early letter categorization ability in the short term (Longcamp, Zerbato-Poudou, & Velay, 2005; James, 2010; Molfese et al., 2011) and supports various academic achievements later (Cahill, 2009; Graham, Harris, & Fink, 2000; Grissmer, Grimm, Aiyer, Murrah, & Steele, 2010; Harvey & Henderson, 1997; Simner, 1982, 1983). Nonetheless, by some accounts, preschool children spend only one minute of their school day in handwriting practice (Pelatti, Piasta, Justice, & O’Connell, 2014). Furthermore, there is mounting evidence that many children with reading disabilities, including dyslexia, also have writing impairments (Berninger, 2006). Neuroscientific research shows that brain mechanisms that support visual letter categorization only respond to letters in pre-literate children after handwriting (printing) practice, but not after visual-auditory (the usually taught method), typing, or tracing practice (James, 2010; James & Engelhardt, 2012; Kersey & James, 2013). Taken together, results suggest a crucial role for handwriting practice in the development of letter categorization ability and of brain networks supporting letter perception and reading.

However, there is a critical gap in our knowledge – we do not know *why* handwriting skill effects letter categorization ability. We have hypothesized that the motor act of producing a letter—stroke by stroke—establishes a connection between the percept of the letter and the motor plan to create the letter, resulting in a visuo-motor system that underlies letter processing (James & Gauthier, 2006; James, 2010, James & Engelhardt, 2012; Kersey & James, 2013). But how does this system serve to facilitate recognition? There are many possibilities, but this study will focus on two theories (not mutually exclusive). The first is that motor information derived from letter production may feed into visual systems through efferent copies to facilitate subsequent letter processing. This idea, in its simplest form, would suggest direct links in the brain between motor systems and visual perception that interact during handwriting. The mechanisms that lead to the facilitation of letter categorization would be localized in neural changes – as long as the motor system is producing letters over time, categorization would be enhanced. Under this hypothesis, any motor act that produces a letter would result in enhanced categorization ability.

Alternatively, it could be the *perceptual output* of the motor act that affects perceptual processing and letter categorization. In this case, the motor system produces a form in the environment that is then perceived by the visual system. That is, the link between handwriting and letter perception emerges from this brain-body-environment interaction. Thus, the mechanism that underlies the brain changes seen when children learn to write letters is caused by the input to the system from the environment. Crucially, the environmental input is created by the brain and body, which changes over time and experience, leading to different environmental inputs depending on physical development of effectors as well as brain development. By this account, the changes in brain systems that occur through development are seen as a part of a larger, dynamic system where the brain, the body, and the environment interact and change one another (for a recent account of this theory see Byrge, Sporns, & Smith, 2014). If environmental input is crucial for shaping

brain systems, then as long as the critical environmental stimuli are perceived, they can serve to influence the larger system.

In the case of handwriting development and its effect on letter perception, we see profound brain changes in the preschool years (James, 2010; James & Engelhardt, 2012; Kersey & James, 2013). During these years, children are just beginning to learn to identify letters, and learning to write by hand. Their handwriting (printing) of letters is messy, and sometimes hardly identifiable (see Figure 1 middle and bottom row for examples). The produced form is therefore, an instance of a letter category that does not conform to a learned category prototype – in the case of letters for preschool children – the upper case sans serif typed form. When the letter is again produced through handwriting, it will be different from the first production (see Figure 1 middle), yet still dissimilar from the letter prototype; Over time resulting in examples of letters that are highly variable, but still belonging to the same category (by virtue of the category label). This perceptual variability, we believe, is key to the facilitative effect that handwriting has on early letter learning. The brain controls the body (that has poor dexterity at this age) to produce the letter (which is messy), resulting in an environmental stimulus (the variable form) that serves to change brain systems (letter representations).

Indirect support for this hypothesis comes from studies that investigate the differences between copying letters and tracing letters. Copying tasks are those where a participant copies, on a sheet of paper, a presented image of a letter. In contrast, although tracing also involves seeing an example, the requirement is to trace over dashes or dots that give the general form of the example letter. Copying tasks have been shown to facilitate handwriting skill better than tracing tasks (Askov & Greff, 1975; Hirsch & Neidermeyer, 1973), and letter processing after copying practice is quite different from processing after tracing. That is, only after copying (and not tracing) does the visuo-motor brain network underlying reading get recruited during subsequent letter perception (James & Engelhardt, 2012). We hypothesize that this difference lies in the output of the motor task – copying results in a variable output of a given letter—whereas tracing results in a prototypical letter-form (see Figure 1 for comparison).

The idea that perceiving variable exemplars of a category can facilitate learning is not new. For example, numerous developmental psychologists have argued that learning a name that applies to variable instances of a category allows the perceiver to compare across instances to detect commonalities and facilitate categorization (Casasola, Bhagwat, & Burke, 2009; Horst, Twomey, & Ranson, 2013; Namy & Gentner, 2002; Samuelson & Smith, 1999; Twomey, Horst, & Morse, 2013; Twomey, Lush, Pearce, & Horst, 2014; Waxman, 2003). This facilitative effect is not only seen in category learning by children, but also when models (Dynamic Field Theory) and robots (iCub) are trained to learn narrow versus variable input and then asked to categorize new input after training (Twomey & Horst, 2011; Twomey et al., 2013).

To successfully identify a symbol as belonging to a particular category, we must ignore irrelevant visual information while focusing on the important aspects of the visual input. With letters, this is not a trivial skill, and can be considered to be one form of object

constancy – the letter ‘A’ is still an ‘A’ despite sometimes dramatic changes in its visual form (i.e. a, A, **a** and *a*). One theory—the “distinctive features” theory—suggests that successful letter recognition and categorization requires the viewer to attend to critical features that remain invariant across transformations and distortions (Gibson & Gibson, 1955; Gibson, Gibson, Pick, & Osser, 1962; Pick 1965). Previous studies have found that, when asked to identify exact matches, preschool children make significant letter recognition errors by extending labels to examples that do not share the same distinctive features (Gibson et al., 1962). This suggests that young children have to learn to identify the invariant critical features that define letter representations. However, these previous studies do not address how children then learn to generalize recognition to variable examples of the same symbol category. Therefore, the focus of the present study is to extend the investigation on letter recognition by examining how young children define symbol categories and incorporate variable visual information. The ability to identify symbols despite changes in visual form is acquired through experience, and writing letters early on is one way that children see highly variable exemplars of a single category.

Thus, the present hypothesis evolved from two disparate literatures: a) that tracing letters is very different from copying letters both in terms of the neural substrates involved (James & Engelhardt, 2012) and in the relative facilitative effects the two productions have on subsequent behavior (Askov & Greff, 1975) and b) that categorization ability is facilitated by learning variable instances of a given category. The present experiment tests the hypothesis that copying symbols by hand serves to provide highly variable instances of a named category during learning and it is this *output* of the motor production that serves to facilitate categorization ability, thereby the brain-body-environment interaction serves to produce the developmental change.

To address this hypothesis, we taught children the names of four Greek symbols through one of six learning conditions. Three of the conditions involved motor production (copying symbols, tracing typed symbols, and tracing handwritten symbols), and the other three involved visual-auditory practice (studying symbols presented in a single typed font, in multiple typed fonts, and in handwritten form). After ensuring that the learning sessions were successful, we tested children’s understanding of the newly learned symbol categories through a card-sorting task.

## Method

### Participants

A total of 72 five-year-olds (36 males;  $M = 66.0\text{mos}$ ,  $SD = 3.5\text{mos}$ ) participated in this study, and children were evenly and randomly assigned across six learning conditions. All were recruited from the same Midwestern middle-class community. Children had no known motor delays—as assessed by the Movement Assessment Battery for Children-2 (MABC-2)—and had normal or corrected-to-normal visual acuity.

All participants were currently enrolled in some form of preschool/kindergarten schooling, had started writing letters at home/school, could write their own names, and were right-hand dominant. Additionally, all children had to meet two main criteria: 1) all children had to

already know and recognize majority (at least 75%) of the letters from the Roman alphabet, and 2) they should not have any prior knowledge of Greek symbols. Knowledge of alphabet letters indicated that they were capable of learning symbol categories, and Greek symbols were used as novel stimuli in the experiment. An additional nine children were excluded from the experiment because they failed to meet the above criteria (e.g. could not recognize more than 75% of the Roman alphabet letters), while another eleven participants were excluded because they did not follow instructions or refused to finish the entire study.

## Materials

Greek symbols were used as stimuli in the present experiment because we were interested in *initial* category learning, but children of this age are already familiar with the Roman alphabet. In addition, Greek symbols are similar to Roman letters in terms of number of strokes, curvature variation, and form. Unlike pseudo-letters, Greek symbols can be typed using a standard word-processing program. Four Greek symbols were used for this experiment: pi ( $\pi$ ), zeta ( $\zeta$ ), psi ( $\Psi$ ), and omega. Omega was referred to as “mega” because piloting data revealed that five-year-old children struggled to remember the original name.

**Testing stimuli**—All materials for the testing tasks were the same across the six learning conditions (copying, tracing typed forms, tracing handwritten forms, viewing single typed fonts, viewing multiple typed fonts, and viewing handwritten symbols).

We used a 4 alternative-forced-choice (4AFC) task to measure learning of the symbols. Stimuli in the 4AFC task consisted of four images presented in a square on a computer monitor: an upright, learned symbol (e.g.  $\Omega$ ); a rotated, learned symbol (e.g.  $\text{Ⓜ}$ ); a geometric shape (e.g.  $\square$ ); & an unlearned Greek symbol (e.g.  $\delta$ ). The Greek symbol fonts differed across displayed trials. Figure 2 displays the warm-up and test trials used in the 4AFC tasks.

A card-sorting task, in which two sets of Greek symbol flashcards were created: typed & handwritten, was used to test categorization ability. There was a total of 32 flashcards for each set (eight flashcards for each symbol). In the typed set, all the flashcards for each symbol were of different typed fonts (Appendix A), and the fonts differed from the flashcards presented in the symbol-learning phase. The handwritten set of flashcards was created by a pilot group of 14 children of the same age range as the participants. These samples were not used in the symbol-learning phase. Therefore, all stimuli to be categorized were novel instances of the newly learned categories. Appendix B displays all the handwritten samples we selected for the symbol-categorization phase. Furthermore, a set of alphabet flashcards (Arial, 150 point, capital font) was used to confirm children’s recognition of the Roman alphabet letters. Note that all handwritten stimuli sampled from children’s productions were presented on grey cardstock, whereas typed examples were printed on white cardstock. Although unfortunate, we do not believe that this background had any effect on our results given the light shade of the grey and absence of evidence that a small change in background would affect learning behaviors.

**Training stimuli**—The remaining materials differed depending on the learning phase for each condition. For all writing conditions (Copying, Tracing-typed, Tracing-handwritten), children printed on 5.5” × 8.5” gray cardstock flashcards with black, fine-tip markers. Gray

cardstock was used to minimize reflection in the video recordings. Each flashcard had an outline of a 3.5" square printed in the center. The outlined square served as a reference space in which participants were asked to write their symbols. Previous piloting revealed that without the box, children tended to write symbols that were too small or unclear. In the Copying condition, the gray cardstock flashcards did not have anything printed inside the outlined square, but in the Tracing-typed and Tracing-handwritten conditions, each flashcard presented a dotted outline of one of the four symbols with some shading connecting the dots (see Figure 3b and c). For all conditions, examples of the Greek symbols were presented in view of the participants for the duration of the learning episode. There was one laminated 4.25" × 5.5" flashcard for each symbol, and for the Copying and Tracing-typed groups, the symbols were printed in Times New Roman, 150-point font (Figure 3a). For the Tracing Handwritten condition, visual guides for the corresponding tracing flashcards were presented during the learning phase (Appendix C).

The remaining three conditions (Single-font, Multiple-font, Handwritten-font) were all visual learning procedures that presented different sets of symbol flashcards. Participants were presented with 16 flashcards (4 of each target symbol). For the Single-font set, all symbols were typed in Times New Roman font. However, font size was different within each set of symbols (Appendix D). For example, the  $\pi$  flashcards featured a 66 point, 150 point, 220 point, and 300 point font exemplars. This manipulation was important to ensure that there was visual variability among examples in this condition – but not the same type of variability as in the Multiple-font learning conditions (i.e. not variability of form). In the design of this experiment, we assumed that processing variable examples of a symbol in terms of font changes was quite different than processing variable examples in terms of size. Nonetheless, it was important to equate the conditions in terms of ‘different’ examples studied to control for possible effects of repetition of exactly the same stimulus, which may affect attention to task.

Participants in the Multiple-typed font learning condition received 16 flashcards of different typed font examples. All symbols were the same font size, but each symbol set consisted of four different font styles. For example, the  $\pi$  flashcards featured Century, Chalkduster, Edwardian Script ITC, and Poplar Std. Appendix E displays all the font styles used in the Multiple-font learning condition. Finally, the Handwritten-font learning condition presented participants with 16 flashcards of handwritten samples (4 of each target symbol) produced by participants from the other conditions as well as participants excluded from the experiment (Appendix C).

## Design

The test tasks were the same for each group and there were six between-subject learning conditions, three of which were visual-motor and three that were purely visual-auditory in nature.

**Visual-motor learning conditions**—These conditions included: Copying—in which the participants copied the symbols onto flashcards from visual examples (Figure 3a); Tracing-typed—using the same examples as Copying, the participants traced each symbol; and



Tracing-handwritten—participants traced handwritten examples of the symbols onto flashcards with visual examples (Appendix C) present throughout learning phase.

**Visual-auditory learning conditions**—Single-font—participants in this group learned the symbols given in a single font style but varied in size (Appendix D). Multiple-font—participants learned multiple-font exemplars of the symbols (Appendix E). Handwritten-font—participants learned handwritten examples of the symbols (Appendix C).

## Procedure

Regardless of learning condition, all participants were asked to complete the experimental tasks in the same order: write own name, ABC recognition, symbol-learning phase, 4AFC, symbol-categorization phase (typed symbols card-sorting, then handwritten symbols card-sorting), & 4AFC again. The instructions for the symbol-learning phase differed across conditions, but all other task procedures were the same. To keep children motivated throughout the study, stickers were handed out after each completed task.

**Write own name**—All participants were first asked to write their own names. This task was to ensure that participants could use the writing instrument provided (a marker) and could produce familiar symbols.

**ABC recognition**—One-by-one, the experimenter introduced the ABC flashcards in random order, and participants were asked to name the letters aloud. They were not corrected if they mislabeled any of the letters. If participants could not correctly identify at least 75% of the alphabet letters, they were excluded from the study.

**Symbol-learning phase**—In this task, the experimenter taught the children the names of the four novel symbols. This is the only portion of the experiment that differed across learning conditions. For the Copying condition, participants were given blank, gray cardstock flashcards with the outlined reference space. Each Greek symbol flashcard (Figure 3a) was presented one-at-a-time. When a flashcard was presented, the experimenter named the symbol (e.g. “This is a psi.”), asked the child to repeat the novel name, and then asked the child to write the symbol inside the outlined square. Participants were asked to produce four examples of each symbol in random order. In the Tracing-typed and Tracing-written conditions, the procedure was the same as the Copying condition, but instead of copying the symbols independently, participants were asked to trace the outlined symbols using the tracing flashcards (Figure 3b and c). The symbols were named and the typed or handwritten sample flashcards were present during the learning procedure. Participants produced 16 traced samples of the Greek symbols (4 of each category). Once all the handwritten and traced samples were created, the experimenter reiterated the symbol names and then shuffled all the flashcards. Participants were asked to re-sort the flashcards back into the four Greek symbol categories, and they had to name the symbol each time they placed a flashcard in the correct pile.

For the visual-only learning conditions, experimenters revealed the flashcards one-by-one, the experimenter named the symbol, and then the children were asked to name each symbol. After all 16 examples were sorted, the flashcards were shuffled and participants were asked

to sort them again, naming each symbol throughout the process. This process was consistent across all conditions.

**Symbol Recognition (4AFC task)**—In each 4AFC task, participants were tested on their ability to point to the learned Greek symbols in the upright position, across different font variations (Figure 2). This is a standard letter recognition task used in previous research (Longcamp et al., 2005; James, 2010). Although often called a ‘recognition’ task, it does not require recognizing the exact symbol learned, but rather to categorize (by pointing) a prototypical instance of a symbol into a named category. We included this task to ensure that participants learned the Greek symbols equally across our conditions. The 4AFC task used here required selecting the target symbol among three distractors: A rotated version of the symbol, an unlearned Greek symbol, and a novel shape. Thus, the child must not only categorize the named symbol (by pointing), but also distinguish it from another similar symbol and understand that orientation is important for category membership. This latter point is important for learning letters as children must learn the unusual notion that if a letter is mirror reversed or misoriented, it may no longer belong to the same category as the correctly oriented letter (that is, if a ‘p’ is rotated upside-down, it becomes a ‘d’). In the present study, we were interested to see whether children would generalize this rule to novel symbols, or whether they would treat these symbols more like other non-letter objects wherein orientation changes do not violate category membership (e.g. a car is a car in every orientation). The 4AFC task was performed both before (initial 4AFC) *and* after (final 4AFC) the card-sorting task, allowing us to measure improvement in 4AFC between initial learning and after repeated exposure to variable examples (through card-sorting).

Each iteration of the task started with the *warm-up* trial, where four geometric shapes were displayed on the screen (Figure 2, top left). The experimenter named each shape one-at-a-time and asked the participant to point to the locations on the screen. This helped participants understand that their answer choices could be located in any one of the four positions. For each *test* trial, there were four choices presented: an upright learned symbol (target), the same learned symbol rotated in a different orientation (misoriented), an unlearned symbol, and a geometric shape. Participants were asked to point to the symbol that was named (e.g. “point to the psi”). If they pointed to multiple choices, the experimenter asked the participants to identify only one symbol that they believe to be the target symbol. If participants claimed that none of the presented symbols were the target symbol, then the experimenter moved on to the next trial. This continued until participants had completed all 12 test trials.

**Symbol-Categorization (Card-sorting task)**—Card-sorting was used as a task here because it is fun and engaging for young learners, they are familiar with this type of task, and it is effective in testing the variations of stimuli that children consider belonging to the same learned category. This latter point is most informative: we can explicitly test the allowable deviations from a prototype during this early stage of learning. As such, there were two separate tasks in this phase: sorting of typed-symbol flashcards & sorting of handwritten-symbol flashcards. All participants sorted the typed-symbol flashcards first. At the start of this task, the experimenter laid out the learned symbols participants saw or



produced during the learning phase. These samples were arranged in the four categories: pi, psi, mega, & zeta. Participants were told that they would be handed additional flashcards that needed to be sorted into the correct piles. If they believed that a flashcard was of one of the four learned symbols, then they should place the card in the right category. However, if they believed that a flashcard did not belong in any of the four symbol categories, they could place the flashcard in a separate pile labeled as the “doesn’t belong” group. Therefore, participants always had a choice of placing each flashcard into one of five possible categories, and they were not obligated to fit any of the cards into one of the four learned categories. We included the ‘doesn’t belong’ category to minimize frustration, therefore not forcing children to choose a category if they were unsure (for support for including this category, see Samuelson & Smith, 1999). After participants finished sorting the typed flashcards (Appendix A), the experimenter asked them to repeat the names of the four Greek symbol categories. Then, the same instructions and procedure was repeated with the handwritten flashcard set (Appendix B). We used these two symbol types (typed and handwritten) to test whether or not children were able to generalize their knowledge about the symbol categories to atypical (handwritten) instances, which were more variable and therefore more challenging to identify.

### **Data Coding & Reliability**

All data were coded through video recordings of experimental sessions, with two experimenters coding all videos independently. Percent agreement between the two coders ranged from 90% to 100%. The ABC recognition task was used to confirm that all participants started at the same level and could correctly identify at least 75% of the alphabet letters. For 23 participants, the capital “I” resembled a lowercase “L”. If they labeled the letter as “L”, we excluded the letter from the total. Because all participants were successful at identifying majority of letters, their responses will be reported but not analyzed.

Only the 4AFC and card-sorting tasks were coded for statistical analyses. For the 4AFC, the “target” answer was always the upright, learned symbols, but a few participants in selected trials refused to select any of the choices and these specific trials were not included in the 4AFC analysis. We also recorded the errors participants made in the 4AFC tasks: the proportion of trials participants selected the misoriented, unlearned, and shape symbol choices. For the card-sorting task, coders determined the proportion of typed and handwritten flashcards participants 1) correctly categorized, 2) incorrectly categorized, & 3) falsely rejected from the learned categories (put into the ‘doesn’t belong’ category). Coders also recorded the duration of the symbol-learning phase to determine if amount of time spent learning the novel symbols affected performance on the categorization tasks. Time codes were considered reliable if the difference between coders’ responses was less than 1 sec, and the two coders were in 91.7% agreement.

## **Results**

### **ABC recognition**

Overall ABC recognition was very high (Range: 76.9%–100%, Mean: 98.4%), indicating that all children could recognize the letters of the alphabet to our criterion.

### Duration of Symbol-learning phase

For all learning conditions, participants were taught four novel symbols through either repeated visual-motor training (Copying, Tracing-typed, Tracing-handwritten) or visual training alone (Single-font, Multiple-font, & Handwritten conditions). Because it takes more time to produce a symbol than to visually study a symbol, we expected differences in training time between conditions. To determine if learning duration differed significantly across conditions, we performed a one-way ANOVA for duration of symbol-learning phase  $\times$  learning condition and found a significant effect,  $F(5,66) = 41.58, p < .01, \eta^2 = .76$ . Bonferroni corrected post-hoc tests revealed that the Copying, Tracing-typed and Tracing-handwritten conditions spent significantly more time on the symbol-learning phase than Single-font, Multiple-font, and Handwritten-font learning conditions (Figure 4). Thus, the visual-motor learning conditions required more time for the learning portion of the study, and as such, we will explore the interaction of this variable with our learning conditions for both learning tasks in the following section.

### Symbol-Recognition tasks (4AFCs)

In these tasks, participants were given the following choices: upright learned symbol (target), misoriented learned symbol, unlearned symbol, and geometric shape. We excluded the trials that participants refused to make a selection. Fourteen participants refused to make a selection on at least one trial, and a total of 33 trials (1.9% of all trials; 17 from the Initial 4AFC) were excluded from the analysis. The reasons for including this task were a) to ensure that all the participants were able to identify the learned Greek symbols above chance, indicating that the learning conditions were successful, and b) to discover whether or not participants were able to understand the importance of orientation for category membership.

To explore how well participants were able to identify the upright target symbols between tasks and conditions, we used a mixed model ANOVA for Time (4AFC Initial vs. Final)  $\times$  Condition (Copying, Tracing-typed, Tracing-handwritten, Single-font, Multiple-font, Handwritten). A significant main effect for time was observed,  $F(1,66) = 20.65, p < .01, \eta_p^2 = .24$ . Participants were more successful at identifying the target symbols (regardless of condition and font style) on the Final ( $M = 83.3\%, SD = 14.1\%, 95\% CI: 80.0\%, 86.7\%$ ) than the Initial ( $M = 75.4\% SD = 16.2\%, 95\% CI: 71.6\%, 79.2\%$ ) 4AFC, illustrating that symbol recognition improved over the experimental session. However, selection of the target symbols on both Initial 4AFC,  $t(71) = 26.47, p < .01$ , and Final 4AFC,  $t(71) = 35.08, p < .01$ , were significantly above chance ( $p = 25\%$ ).

The mixed-model ANOVA also revealed a significant interaction for Time  $\times$  Condition,  $F(5,66) = 2.76, p < .05, \eta_p^2 = .17$ , with only certain conditions demonstrating a significant improvement in symbol recognition. Specifically, Copying,  $t(11) = 2.89, p < .05$ , Tracing-typed  $t(11) = 3.31, p < .01$ , Single-font,  $t(11) = 3.41, p < .01$ , and Multiple-font,  $t(11) = 2.87, p < .05$ , participants correctly identified the learned symbols significantly more on the Final 4AFC test compared with the initial test (Figure 5). However, no significant main effect was observed for overall condition ( $p > .1$ ). Because of the interaction, we ran one-way ANOVAs on the initial and final testing sessions separately. Importantly, there was no

difference across groups in the Initial ( $F(5,66)=1.84, p=.11$ ), or Final ( $F(5,66)=1.79, p=.12$ ) tasks, demonstrating that the learning conditions did not, in themselves, affect performance, but the card-sorting task (between the two 4AFC tests) improved performance in some groups but not others. Specifically, only the two conditions where handwritten samples were given to the participants (Tracing-handwriting and Handwritten-font) did not improve performance from the first 4AFC to the second.

Furthermore, we examined whether there were significant relationships between duration of learning phase and responses on the Initial and Final 4AFC. Correlations between learning time and Initial 4AFC ( $r = .08, p > .1$ ) and learning time and Final 4AFC ( $r = -.04, p > .1$ ) did not yield any significant relationships, indicating that successful recognition of the learned symbols was not due to amount of study time in the learning phase.

**Error analysis**—For each 4AFC trial, participants were presented with three distractors: misoriented learned symbol, unlearned symbol, and geometric shape. Although participants were highly successful at identifying the target answers, they still made errors on the Initial and Final 4AFC tasks. For the Initial 4AFC, participants selected the misoriented learned symbol on 20.6% of trials, the unlearned Greek symbol on 3.1% of trials, and the geometric shape on 1.4% of trials. For the Final 4AFC task, participants chose the misoriented learned symbol on 14.3% of trials, the unlearned symbol on 1.9% of trials, and the geometric shape on 0.7% of trials.

For the Initial 4AFC task, a mixed-model ANOVA for Error (misoriented, unlearned, vs. shape symbols)  $\times$  Condition revealed a significant main effect for error,  $F(1.24,82.01) = 82.30, p < .01, \eta_p^2 = .56$ , with adjustments made for non-sphericity using the Greenhouse-Geisser adjustment factor. Participants made more misoriented errors than unlearned symbol and geometric shape errors. On the Final 4AFC task, the same mixed-model ANOVA also revealed a significant main effect for error,  $F(1.24,82.01) = 69.46, p < .01, \eta_p^2 = .51$ , with adjustments made for non-sphericity using the Greenhouse-Geisser adjustment factor. Participants continued to make more misoriented errors than unlearned symbol and geometric shape errors (Figure 6). Although errors were low, the results suggested that participants made orientation errors more than other types in both Initial & Final 4AFC tasks. No significance was observed for any other main effects or interactions (all  $p > 0.1$ ). Thus, there was no difference among the groups in the types of errors that were made as participants consistently made the most errors by selecting the misoriented symbol.

### Symbol Categorization tasks (Card-Sorting)

To determine if there were any differences across learning conditions in regards to categorization behavior, we performed a mixed-model ANOVA for Card type (handwritten vs. typed flashcards)  $\times$  Condition (Copying, Tracing-typed, Tracing-handwritten, Single-font, Multiple-font, Handwritten) for correct categorization responses. We found significant main effects for card type,  $F(1,66) = 110.26, p < .01, \eta_p^2 = .63$ , and condition,  $F(5,66) = 6.78, p < .01, \eta_p^2 = .34$ . Participants were more successful at correctly sorting the typed symbols ( $M = 84.5\%, SD = 1.8\%, 95\% CI: 80.3\%, 88.7\%$ ) than handwritten symbols ( $M = 65.5\%, SD = 2.0\%, 95\% CI: 60.7\%, 70.3\%$ ). Further, one-sample t-tests revealed that

correct categorization for both card types were significantly above chance ( $p = 20\%$ ), typed:  $t(71) = 30.69, p < .01$ , handwritten:  $t(71) = 18.91, p < .01$ .

The main effect of condition was due to the Tracing-typed group and the Single-font group performing with less accuracy than the other groups. Bonferroni corrected post-hoc tests revealed that participants from the Tracing-typed group sorted significantly fewer flashcards into the correct symbol categories than those in the Copying, Tracing-handwritten, Multiple-font and Handwritten-font groups. Further, the Tracing-handwritten group sorted significantly more flashcards than the Single-font condition (Figure 7). There was no significant interaction of Card-sorting type  $\times$  Group ( $F(5,66) = .63, p = .6$ ): participants from all conditions were similar in their ability to correctly categorize typed versus handwritten cards.

Furthermore, we examined whether there were significant correlations between learning time and correct card-sorting of typed,  $r = .06, p > .1$ , and handwritten,  $r = .21, p > .05$ , flashcards, but no significant effects were found. This demonstrated that correct categorization of novel symbol examples was not related to the duration of the training period, and the significant difference in correct responses observed between conditions was not due to participants taking longer to complete the learning phase in certain conditions.

**Error analysis**—For the card-sorting tasks, there were also potential errors in how participants categorized the symbols. Specifically, if they sorted the symbols incorrectly in one of the learned categories or rejected an example as a learned symbol, then they would have made categorization errors. For handwritten flashcard error categorization, a mixed-model ANOVA for Error type (incorrect categorization vs. rejection)  $\times$  Condition revealed significant main effects for error type,  $F(1,66) = 82.94, p < .01, \eta_p^2 = .56$ , and condition,  $F(5,66) = 5.20, p < .01, \eta_p^2 = .28$ , and significant interaction for Error type  $\times$  Condition,  $F(5,66) = 5.94, p < .01, \eta_p^2 = .31$ . The results revealed that participants made more rejection errors ( $M = 29.2\%$ ,  $SD = 22.6\%$ ,  $95\% CI: 23.9\%, 34.6\%$ ) than incorrect sorting errors ( $M = 5.3\%$ ,  $SD = 5.4\%$ ,  $95\% CI: 4.1\%, 6.6\%$ ). Bonferroni corrected post-hoc comparisons indicated that Single-font participants made more errors than Tracing-handwritten participants, and Tracing-typed participants made more errors than Handwritten and Tracing-handwritten participants (Figure 8). Thus, less variable visual and visual-motor learning conditions made more symbol categorization errors than more variable learning conditions. Finally, follow-up one-way ANOVAs for each error type by condition revealed that there were significant differences in rejection errors across conditions,  $F(5,66) = 5.94, p < .01, \eta_p^2 = .31$ . Specifically, Tracing-typed participants made significantly more rejections than Tracing-handwritten, Multiple-font and Handwritten conditions; and the Single-font participants made more rejections than Tracing-handwritten condition (Figure 8a). Thus, the groups that made the most errors were those that learned (through visual-motor or visual-auditory) single font examples of the symbol categories.

For typed flashcard error categorization, the mixed-model ANOVA for Error type (incorrect categorization vs. rejection)  $\times$  Condition also revealed significant main effects for error type,  $F(1,66) = 67.50, p < .01, \eta_p^2 = .51$ , condition,  $F(5,66) = 5.84, p < .01, \eta_p^2 = .31$ , and a significant interaction for Error type  $\times$  Condition,  $F(5,66) = 6.38, p < .01, \eta_p^2 = .34$ . Similar

to the errors made in the handwritten card-sorting task, participants made significantly more rejection errors ( $M = 29.2\%$ ,  $SD = 22.6\%$ ,  $95\% CI: 23.9\%, 34.6\%$ ) than incorrect sorting errors ( $M = 5.3\%$ ,  $SD = 5.4\%$ ,  $95\% CI: 4.1\%, 6.6\%$ ). Additionally, Bonferroni corrected post-hoc comparisons revealed that Tracing-typed participants made more errors sorting the typed flashcards than all other participants except Single-font learning condition (Figures 8a, 8b). Specifically, follow-up one-way ANOVAs for each error type by condition indicated that there were significant differences in rejection errors across conditions,  $F(5,66) = 6.13$ ,  $p < .01$ ,  $\eta^2 = .32$ . The results revealed that Tracing participants made more rejection errors than all other conditions except the Single-font learning condition (Figure 8b).

Overall, very few cards were sorted in the wrong symbol categories, which illustrated that the participants determined the majority of symbol examples to be identifiable (placed in the correct categories) or not identifiable (placed in the “doesn’t belong” category). In short, for both typed and handwritten symbol-sorting tasks, the two groups that stood out as performing with the lowest accuracy (Tracing-typed & Single-font conditions) were the ones that learned the symbol categories with the least variable examples.

### Analysis of variability of produced forms

Because our hypothesis rested on the notion that copying resulted in more variable forms than tracing typed forms, we measured the variability in produced symbols for the three writing groups. To assess variability, we measured the amount of deviation in each produced form relative to the exemplar studied. We first overlaid each produced symbol onto the exemplar that was given to either copy or trace. The Copying and Tracing-typed condition exemplar symbols each had 6–7 ‘anchor points’ (Figure 9a), while the Tracing-handwritten condition exemplar symbols had between 6–13 ‘anchor points’ (Figure 9b).

Anchor points were placed at locations where line segments/strokes ended, intersected with another line, or changed direction. These points were chosen because they helped to define the shape of the symbols. We used the most central anchor point to overlay the produced image onto the exemplar. Then, at each of the other anchor points, we measured the amount, in millimeters, that the produced image deviated from the exemplar image. Scoring was as follows: For each deviation greater than 5 mm, 2 points were given, for each deviation from 1–5 mm, 1 point was given. For deletions of any part of the exemplar, 1 point was given, and for any additions made to the produced form relative to the exemplar, 1 point was given. Therefore, for each produced form for every child, a score was given, where higher the score, the greater the deviation from the exemplar. Then for each participant, we averaged the scores from each symbol produced, resulting in an average deviation score for each participant. We then ran a one-way ANOVA to determine whether the participants in the Copying condition did indeed produce more variable symbol forms relative to the participants in the Tracing-typed and Tracing-handwritten conditions. Indeed, the ANOVA revealed a significant effect,  $F(2,33) = 104.22$ ,  $p < .01$ ,  $\eta^2 = .86$ , with the Copying group ( $M = 7.1\text{mm}$  deviation,  $SD = 0.9\text{mm}$ ,  $95\% CI: 6.5\text{mm}, 7.6\text{mm}$ ) producing forms that deviated more from the studied exemplars than the Tracing-typed ( $M = 2.1\text{mm}$ ,  $SD = 0.7\text{mm}$ ,  $95\% CI: 1.7\text{mm}, 2.5\text{mm}$ ) and Tracing-handwritten ( $M = 1.9\text{mm}$ ,  $SD = 1.3\text{mm}$ ,  $95\% CI: 1.1\text{mm}, 2.7\text{mm}$ ) groups.

## Discussion

Letter knowledge is a strong predictor of reading success (Scanlon & Vellutino, 1996), and previous literature has demonstrated that handwriting experience facilitates letter categorization ability in young children (James 2010; Longcamp et al., 2005) and sets up the neural systems that underlie reading (James, 2010; James & Engelhardt, 2012). Therefore, it is important to understand *why* handwriting practice is such a powerful learning tool, especially in comparison to other letter-learning techniques.

Here we compared categorization performance after children learned novel, Greek symbols through 6 different conditions: Copying the symbols, Tracing a typed symbol (single font style), Tracing a handwritten symbol, viewing symbols presented in a single font, viewing symbols presented in multiple fonts, and viewing symbols presented in handwritten form. All children were able to learn the Greek symbol categories as revealed by a 4AFC test. However, when children had to sort a variety of examples of the Greek symbols after their learning, differences among the learning conditions emerged. Specifically, all groups that studied multiple instances of the Greek symbols during learning – whether those were self-produced or simply learned by visual inspection – performed better than the groups that were exposed only to a single, prototypical example of the symbols. Note that the number of instances learned was constant as all groups received the same amount of exposure, but the range of forms they perceived significantly influenced their performance. Before discussing these findings further, we first outline some limitations to the current results.

### Duration of learning episode

It is possible that the effect of writing experience on symbol learning was influenced by the amount of time participants spent during the learning phase. Analysis of the symbol-learning phase revealed that participants in the writing conditions spent significantly more time learning the symbols than those from the visual learning conditions. This would suggest that the writing participants received a learning advantage that affected their understanding of symbol categories. However, there are a few reasons why we believe that duration of learning did not have an effect on subsequent categorization. First, our correlational analyses between learning duration and outcome showed no significant relationships. Second, conditions that had the same learning duration did show differences in categorization ability. That is, although the three motor conditions took the same amount of time during learning, they revealed very different results. Similarly, the three visual conditions, again taking the same amount of time during learning, also revealed different results from one another. Therefore, we are quite confident that learning duration did not significantly affect the results reported here.

### Differences in Initial vs. Final 4AFC performance

All groups benefitted from the card-sorting task in terms of their ability to point to a learned symbol in a forced-choice task except two: the Tracing-handwritten (visual & motor) and the Handwritten-font (visual only) groups. This begs the question of why these two groups did not show any improvement in symbol recognition. This lack of effect was not due to ceiling performance on the Initial 4AFC, and their performance did not go down after card-



sorting; it simply did not change. These were the only two groups that studied handwritten forms that they did not produce themselves. Perhaps studying handwritten stimuli without producing them did benefit symbol recognition, even with increased exposure. Alternatively, because initial recognition was high for both groups, perhaps learning through variable handwritten samples generated broad, inclusive symbol categories that were maintained throughout the study. Although this lack of effect does not take away from the primary findings in the card-sorting task, it does require further consideration and empirical work to discover if there is something different about learning handwritten symbols without self-production.

Nonetheless, the above limitations do not significantly diminish the primary findings from this work: That perceiving variable instances during learning, *regardless of the manner in which the instances were learned*, facilitated categorization compared to learning singular examples of symbol categories. This is not to say that producing symbols and letters by hand is not important. On the contrary, variable symbols are produced in everyday life through handwriting, and therefore it is important that children produce symbols early on, where the output of their bodies will create ‘messy,’ variable instances of categories. This will not occur with keyboarding or tracing, where the typed/traced symbol is presented in a constant (usually prototypical) font.

These findings reveal why tracing practice results in a) different brain activation patterns than copying letters during letter perception tasks (James & Engelhardt, 2012) and b) poorer letter knowledge ability (e.g. Askov & Gref, 1975). That is, when children trace letters, they produce non-variable forms and only perceive a prototypical example of a letter (or symbol). Similarly, when children are taught to ‘see and say’ letter of the alphabet that are prototypical (usually upper case, sans serif letters) they may not learn them as well as if they are given many different examples of letters (for letters, this is an empirical question that has not yet been addressed). These are the two most common ways children learn letters in preschool (Pelatti et al., 2014). They are also the two conditions that performed the worst in our symbol categorization task here. The present results may also explain why typing practice does not facilitate letter recognition to the same degree as handwriting practice (Longcamp et al., 2005), but our results suggest that letter categorization ability would be enhanced with increased handwriting practice and/or learning multiple examples of letters in various ways.

In this study, we were most interested in young children’s ability to form perceptual categories. To recognize many instances of a given letter we must form a perceptual category that includes variable instances of a given letter. In doing so, we extract commonalities, or distinctive features, among category members (e.g. All members of the category “P” must include a vertical line and a half circle at the top of the line directed to the right), but we must also detect differences in perceptually similar instances that do not share the relevant features (a lower case d shares many features with ‘p’, but the semi-circle must face left instead of right. But the upper case D differs in other ways). Defining the constraints on letter categories may be more difficult for some letters than others and therefore may have groups of features that define the category (A’s can either be a triangle with a horizontal line across the center or an oval with a lower right hand tail). Across early

development, children learn to identify distinctive features that define a specific symbol category (Gibson et al., 1962), but successful letter recognition depends on children's abilities to extract these invariant properties across variations. The findings from this study suggest that this skill development is influenced by visual learning experience. With exposure to variable examples of a symbol category, preschoolers learn to focus on definitive features while ignoring inconsequential changes.

There are several ways to describe how category learning occurs, which are beyond the scope of this paper (see Ashby & Maddox, 2005 for review). However, it is important to note that when testing perceptual category learning in children, research has shown that exposure to multiple, variable exemplars leads to better category generalization (Gentner & Namy, 1999; Namy & Gentner, 2002). Intuitively, this makes sense; it would be difficult to learn the parameters of category membership through exposure to a single instance, or to multiple instances that are all perceptually similar. The results suggest that not only are young children capable of identifying the critical features that define symbol categories during learning, but they also are attuned to type of information that is and is not relevant for identifying variable symbol forms. Learning through comparison across different category exemplars appears to be crucial for defining object categories (Gentner, Loewenstein, & Hung, 2007; Graham, Namy, Gentner, & Meagher, 2010). In our view, letter recognition requires this comparison process, and the current study supports the notion that category learning is facilitated by exposure to multiple, variable exemplars.

The route to exposure to multiple letter exemplars can be provided through early handwriting. Because of the physical development of their bodies and brains, preschool children have difficulty accurately reproducing complex 2-dimensional symbols with a writing tool. Although educators may see this as a drawback, therefore encouraging other ways to produce letters (e.g. keyboarding or drawing in sand), we believe that this inaccuracy may be important for the understanding of letter categories. To put it in another way, the developing neural systems in the young child drive the immature hand and finger dexterity to produce an image that is to be perceived and categorized based on an adult-given label. The produced form – a perceptual object in the environment- drives change in perceptual categorization, and in doing so, changes the underlying neural networks subserving categorization. This brain-body-environment interaction is a crucial component in driving developmental change.

In sum, we propose that the reason handwriting supports letter recognition is because it produces variable perceptual symbols in the environment that serve to enhance category understanding. This idea was supported by the findings that 1) Both handwriting, and tracing, of *handwritten* symbols resulted in better categorization than tracing *typed* symbols, 2) That visual study of variable forms (both multiple typed fonts and handwritten symbols) also facilitated categorization to the same extent as handwriting and tracing handwriting, & 3) Conversely, the only conditions that were significantly worse during categorization were those where the participants learned a single font-type of the symbols (single-font learning and tracing-typed).

The practical applications of these findings are significant: if learning symbol categories through multiple exemplars is the key to enhanced categorization, then perhaps learning letters through these methods will facilitate letter categorization ability in young children. This could be implemented in several ways: 1) Increase handwriting practice in the preschool and early elementary school years; 2) Increase tracing of variable examples of letters—either different fonts or handwritten examples; 3) Change the type of visual-auditory learning that is practiced in preschool. Typically, preschool children learn one form of a letter, usually a sans serif upper case letter, but this may not be as effective for letter learning as identifying several different examples of a given letter; 4) Limit single-font exposure learning. With increased keyboarding in the early elementary school years, children may be even more susceptible to developing more restricted symbol categories. When teaching children keyboarding skills, there should perhaps be a script that changes the font letter-by-letter. In this way, through keyboarding, children would also be exposed to multiple fonts.

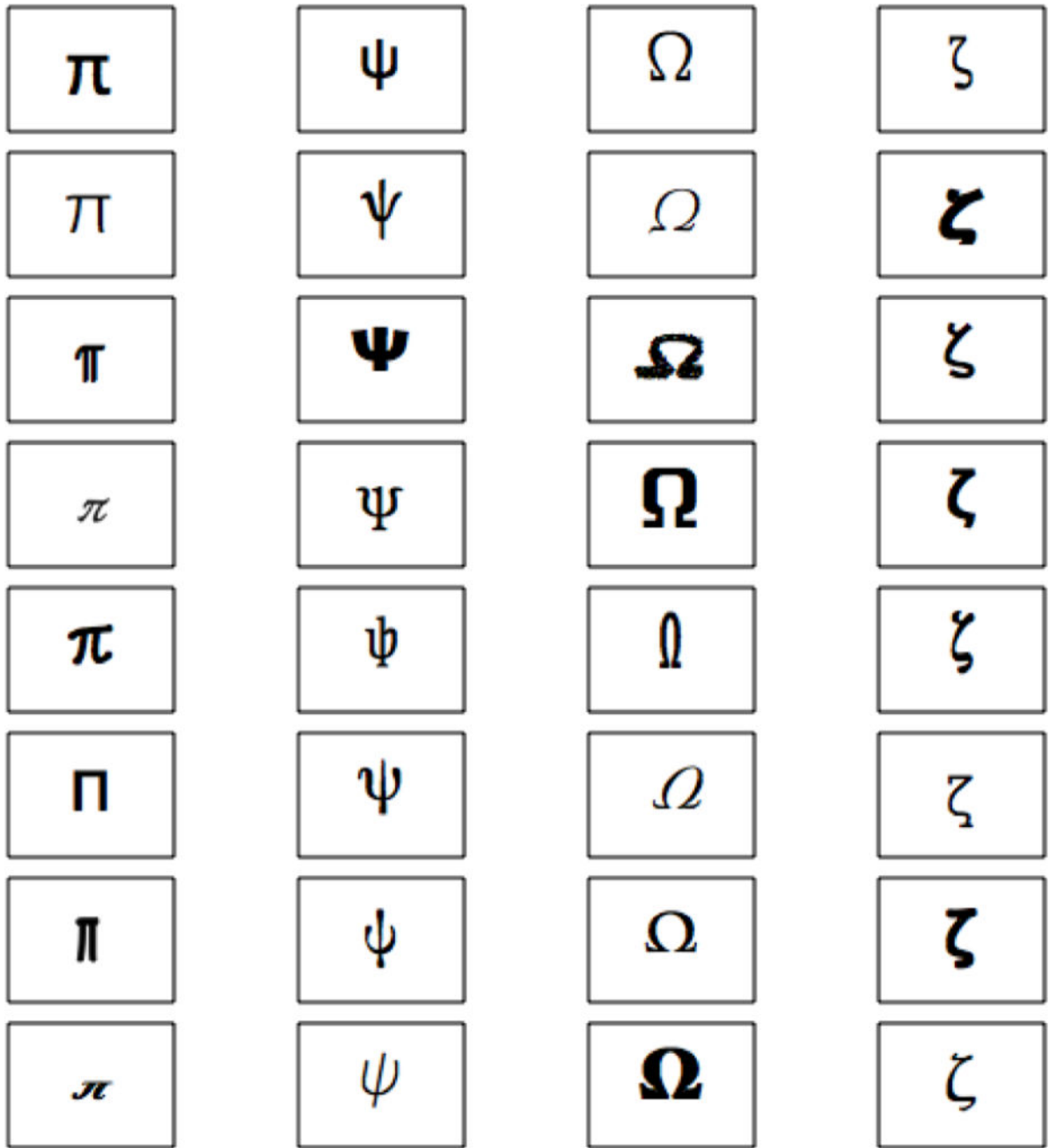
Further studies in the classroom and laboratory would test the feasibility of these ideas, and whether they will help children with letter categorization early on, and facilitate subsequent reading acquisition through enhanced letter knowledge skills.

## Acknowledgments

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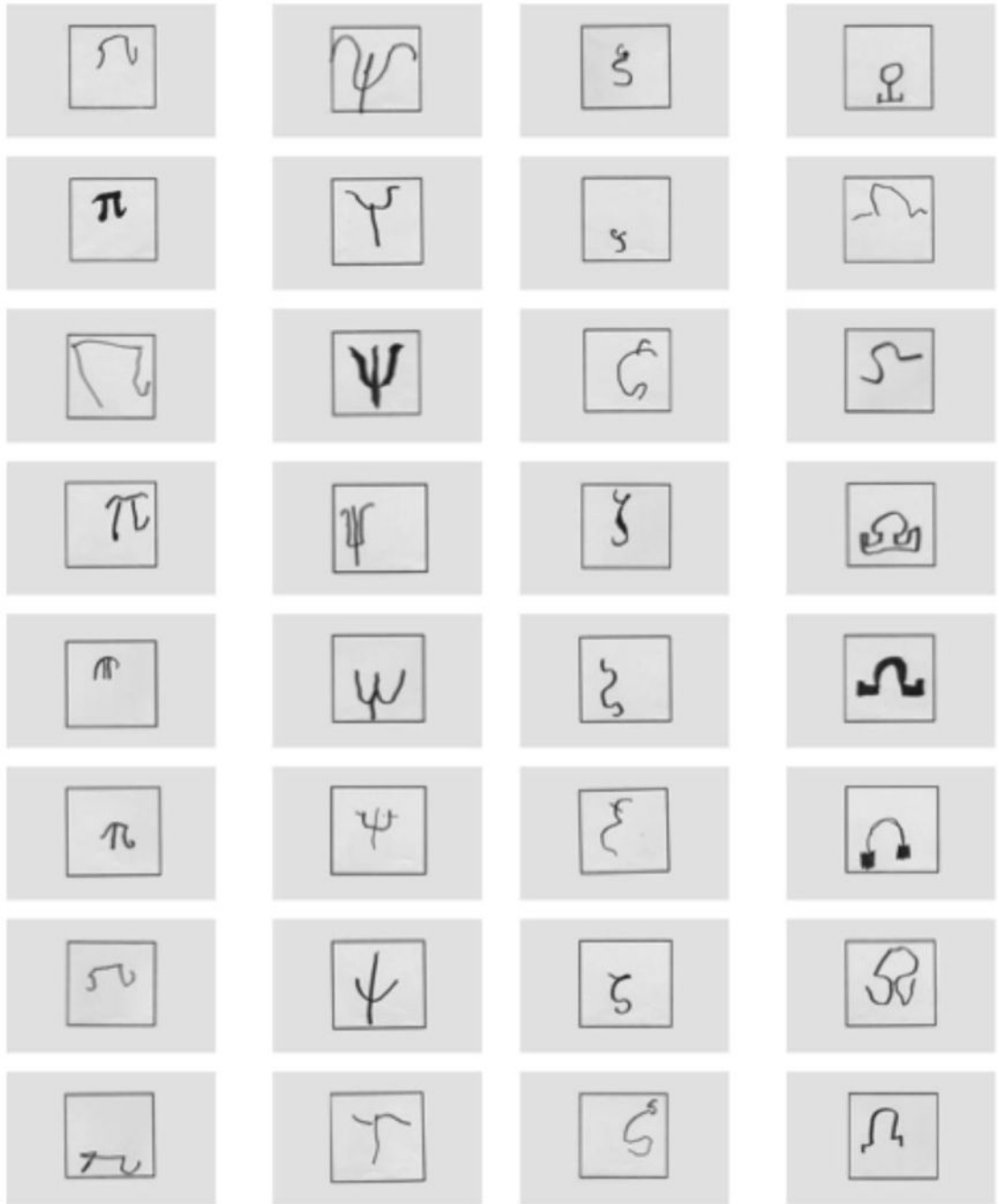
## Appendix A

Typed Greek symbol flashcards used in the symbol categorization (card-sorting task).



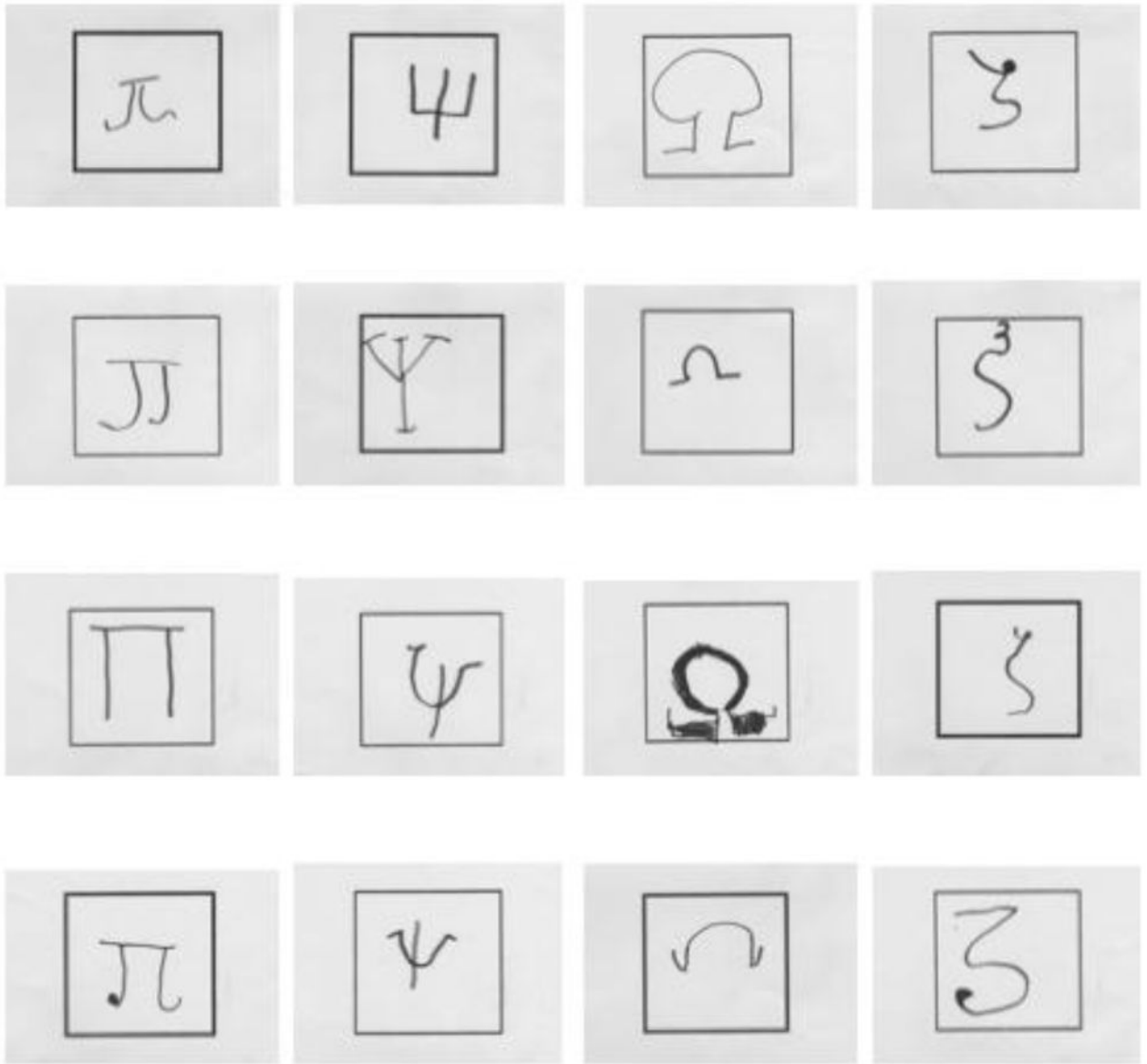
## Appendix B

Handwritten Greek symbol flashcards used in the symbol categorization (card-sorting task).



## Appendix C

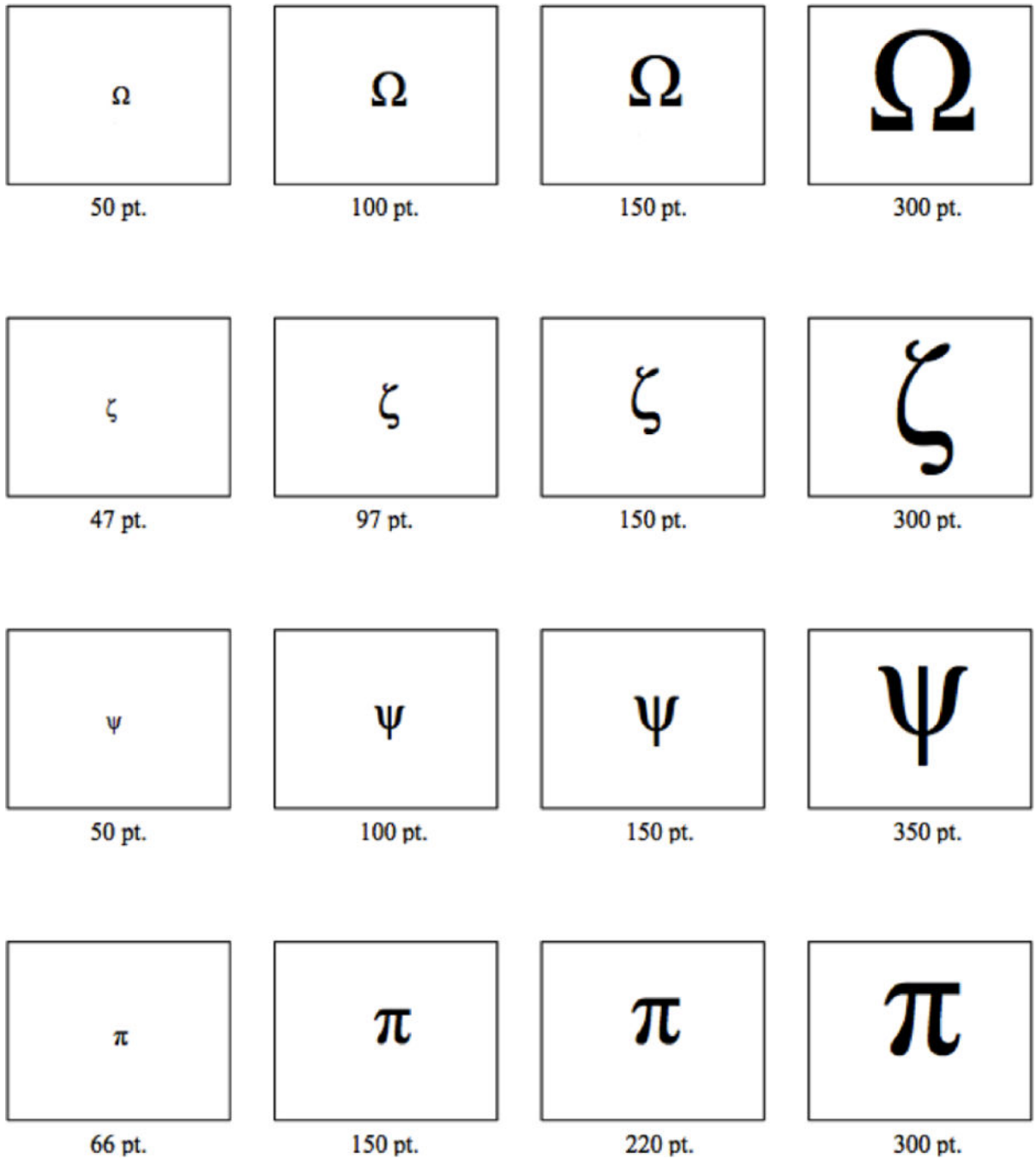
Flashcards used in the symbol-learning phase for the Tracing-handwritten and Handwritten-font learning conditions.



### Appendix D

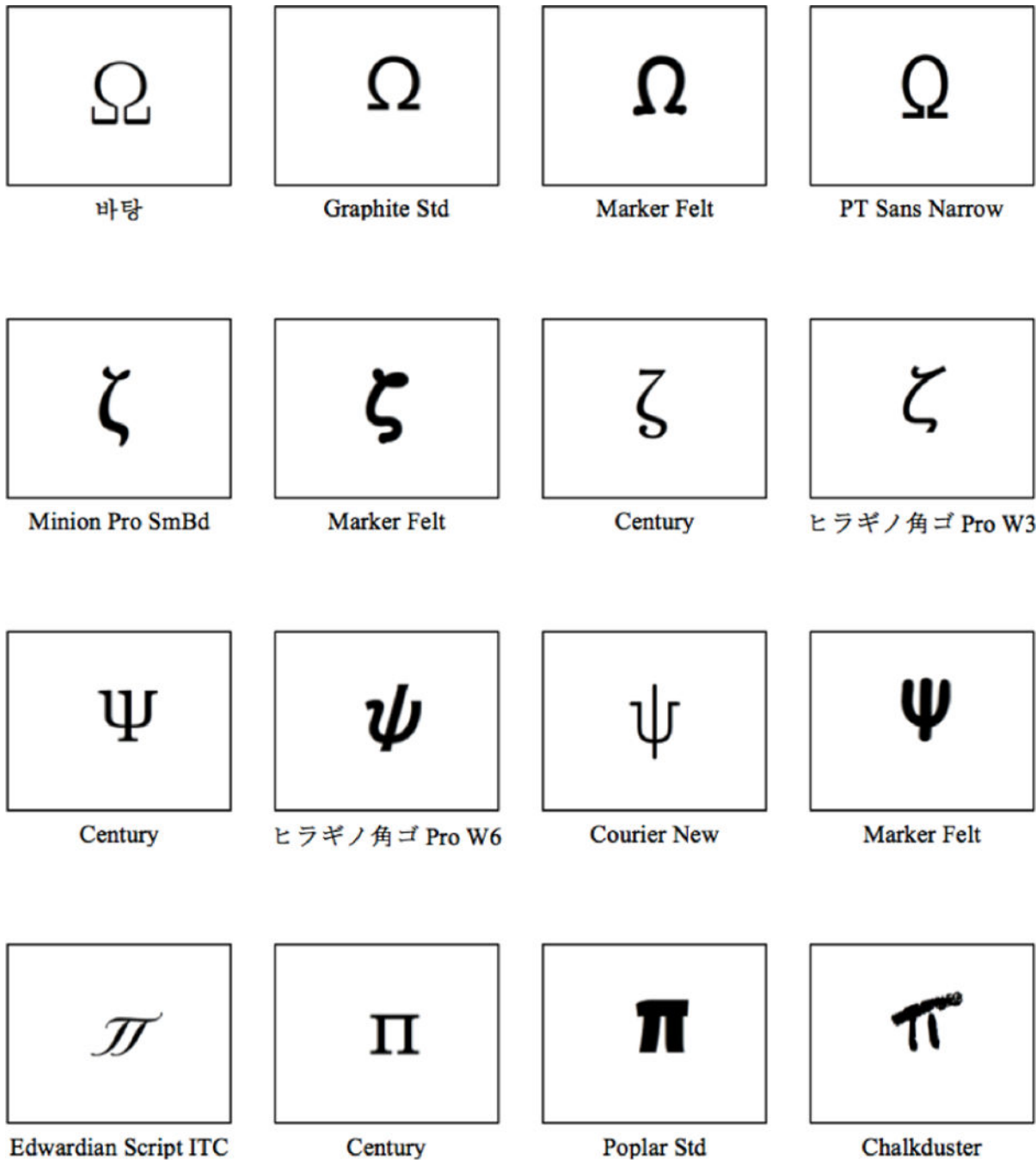
Flashcards used in the symbol-learning phase for the Single-font learning condition.





## Appendix E

Flashcards used in the symbol-learning phase for the Multiple-font learning condition.



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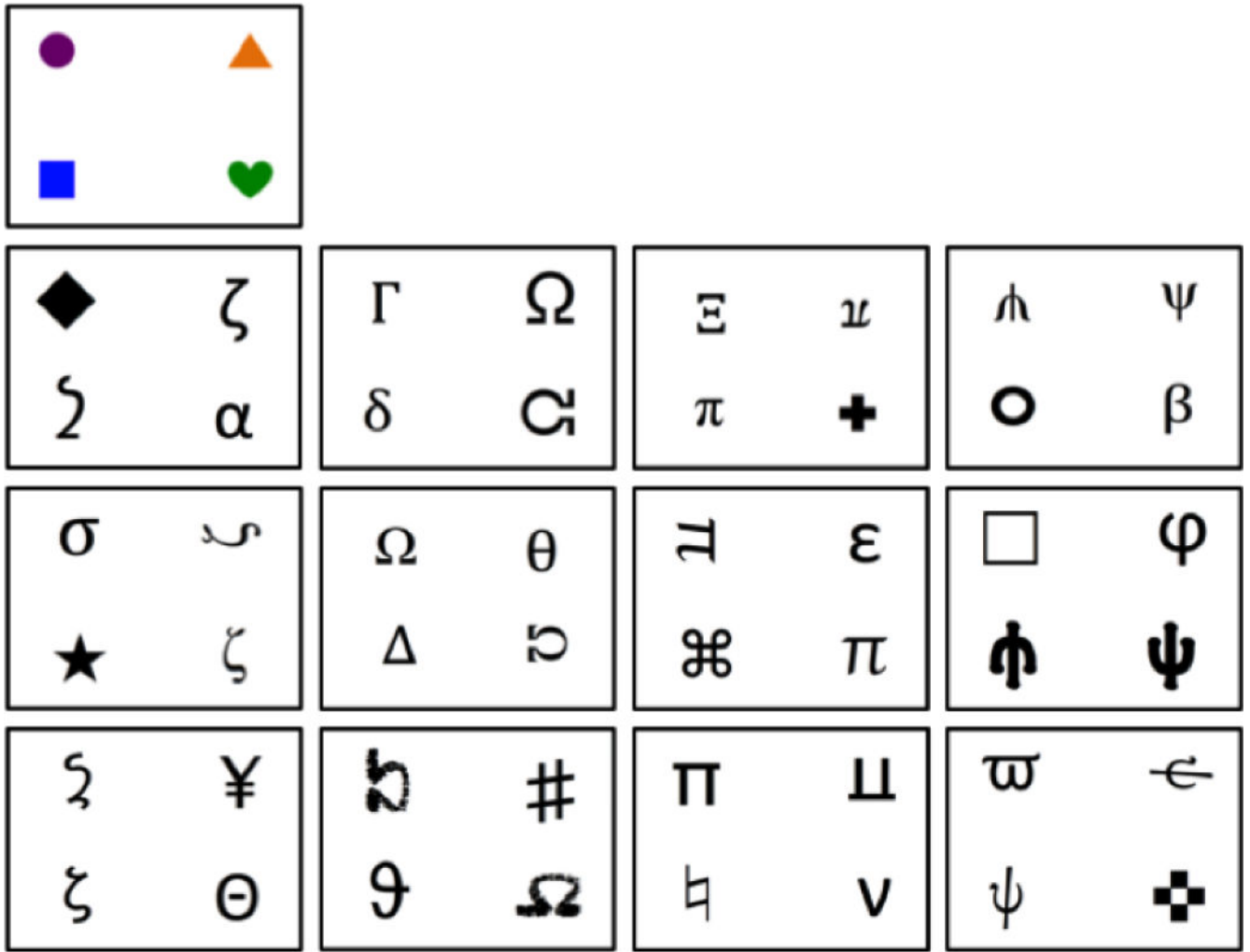
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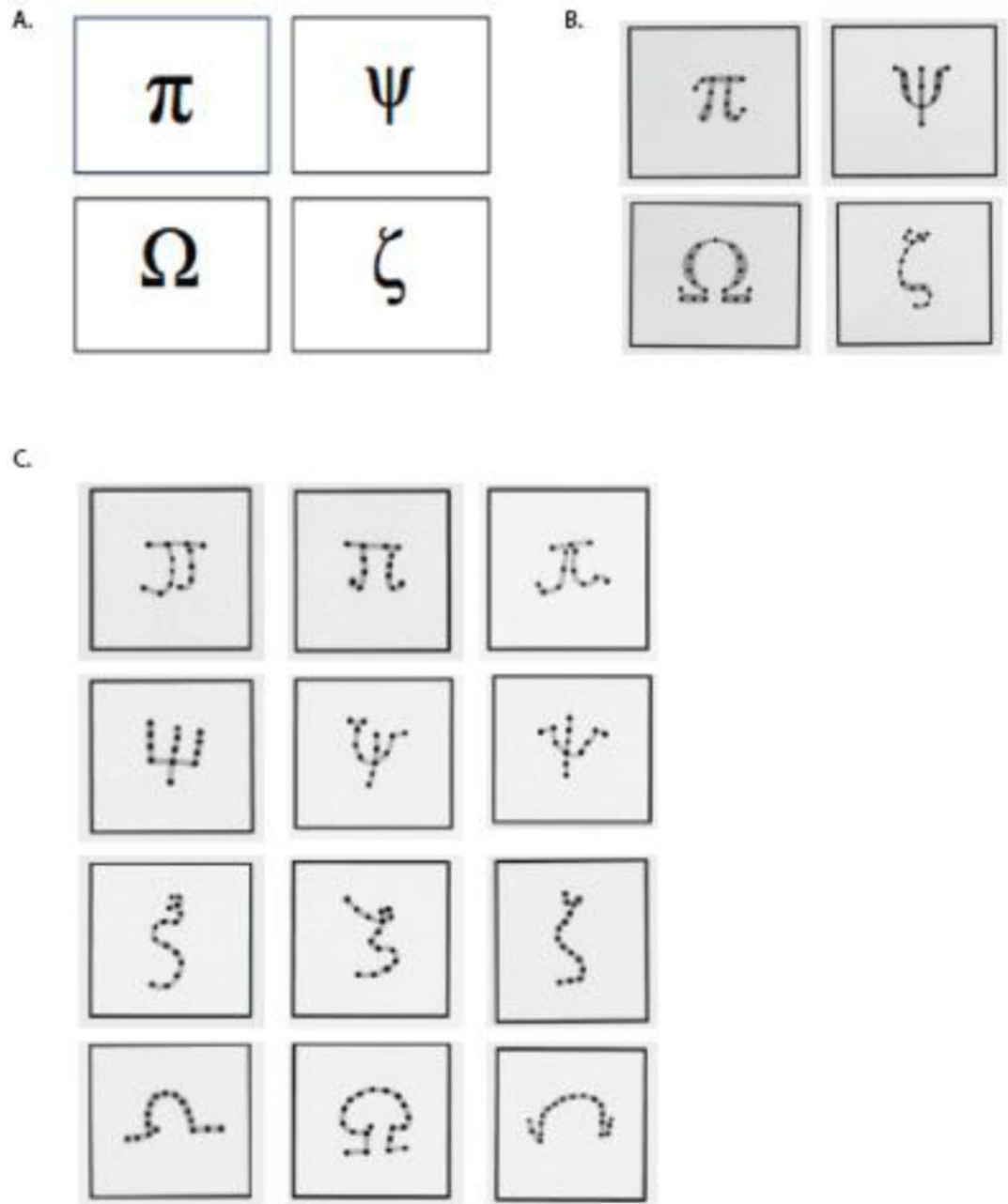
**Figure 1.** Examples of 4-year olds tracing and copying letters. Top row: Tracing the letter 'S'. Middle row: A single 4-year old producing the letter 'E' three times through copying an example. Bottom row: Three different 4-year olds copying the letter 'S' from an example.



**Figure 2.**

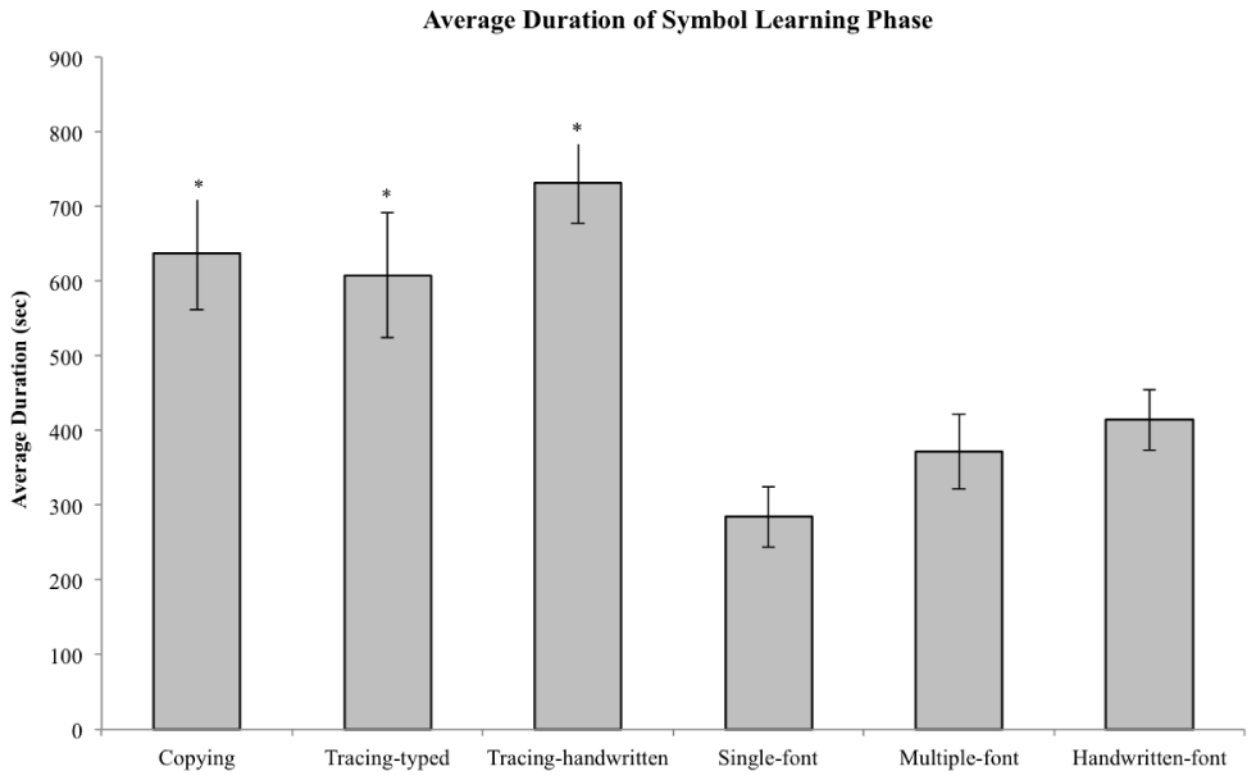
Top left corner: warm-up trial example for 4AFC task. Remainder slides are examples of the 4AFC task trials (see text for details).



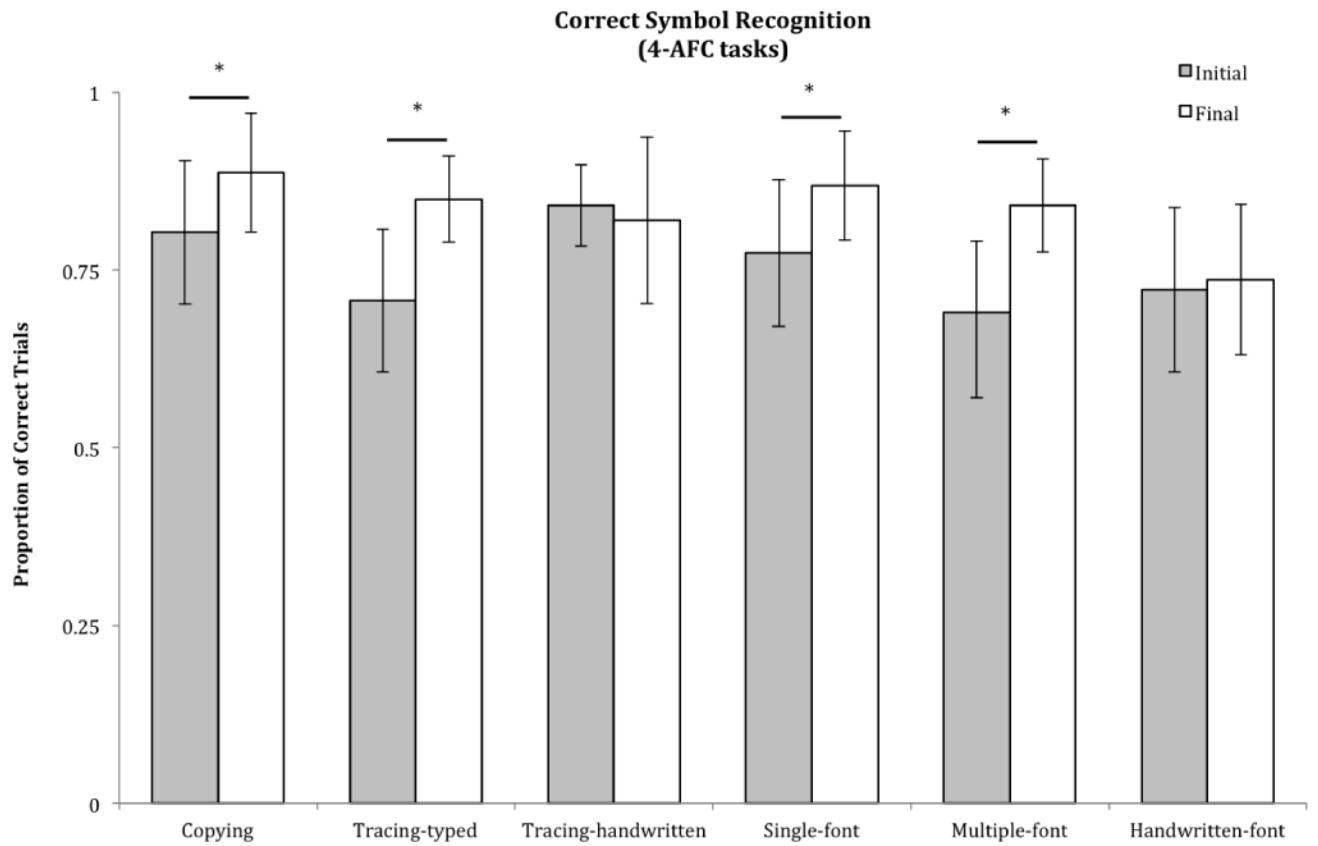


**Figure 3.**

A. The visual examples that were used in the copying, tracing-typed, and single fonts conditions. B. An example of the tracing-typed cardstock guides. C. Examples of the tracing-handwritten cardstock guides.



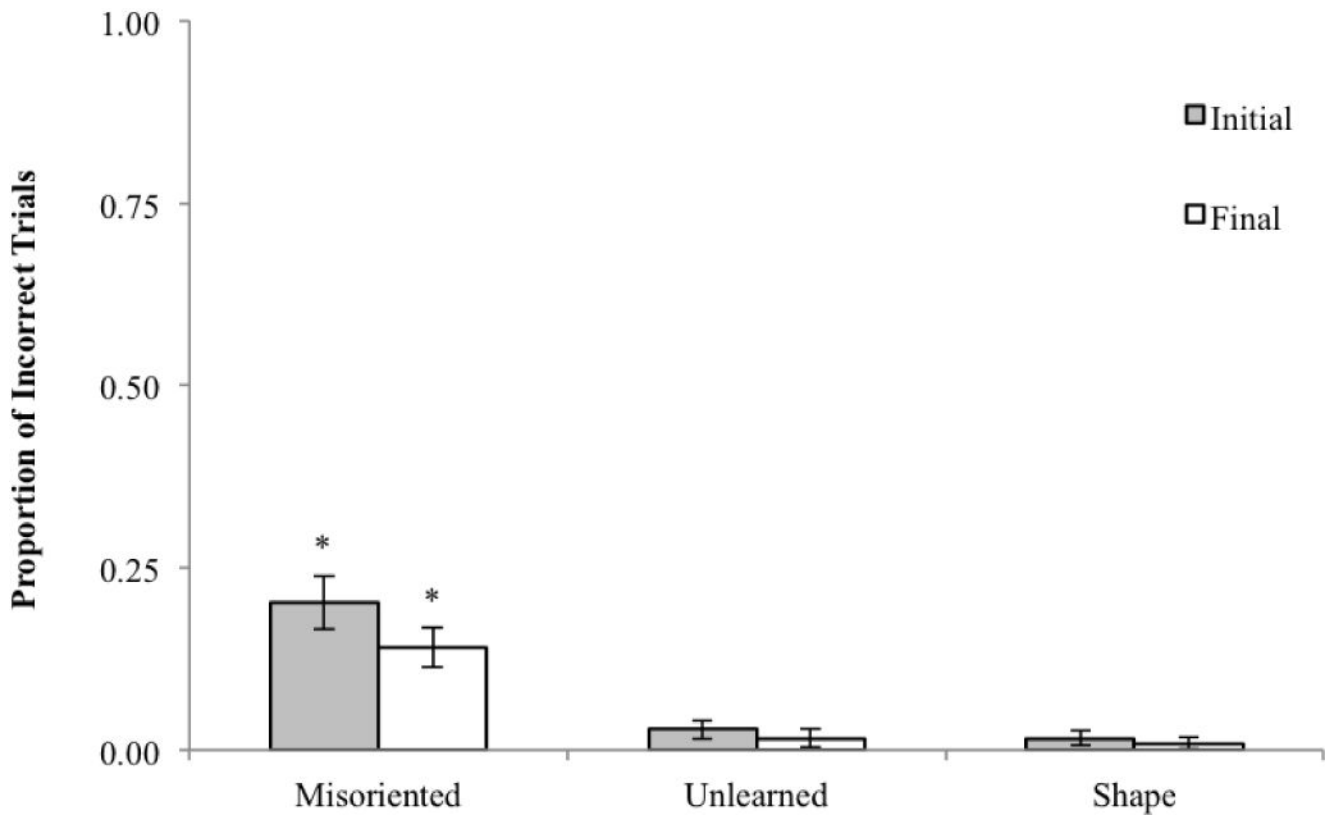
**Figure 4.** Duration of symbol learning phase across conditions. Participants in the symbol production groups had significantly longer learning phase durations than those in the visual only learning groups. All errors bars in all figures depict 95% confidence intervals.



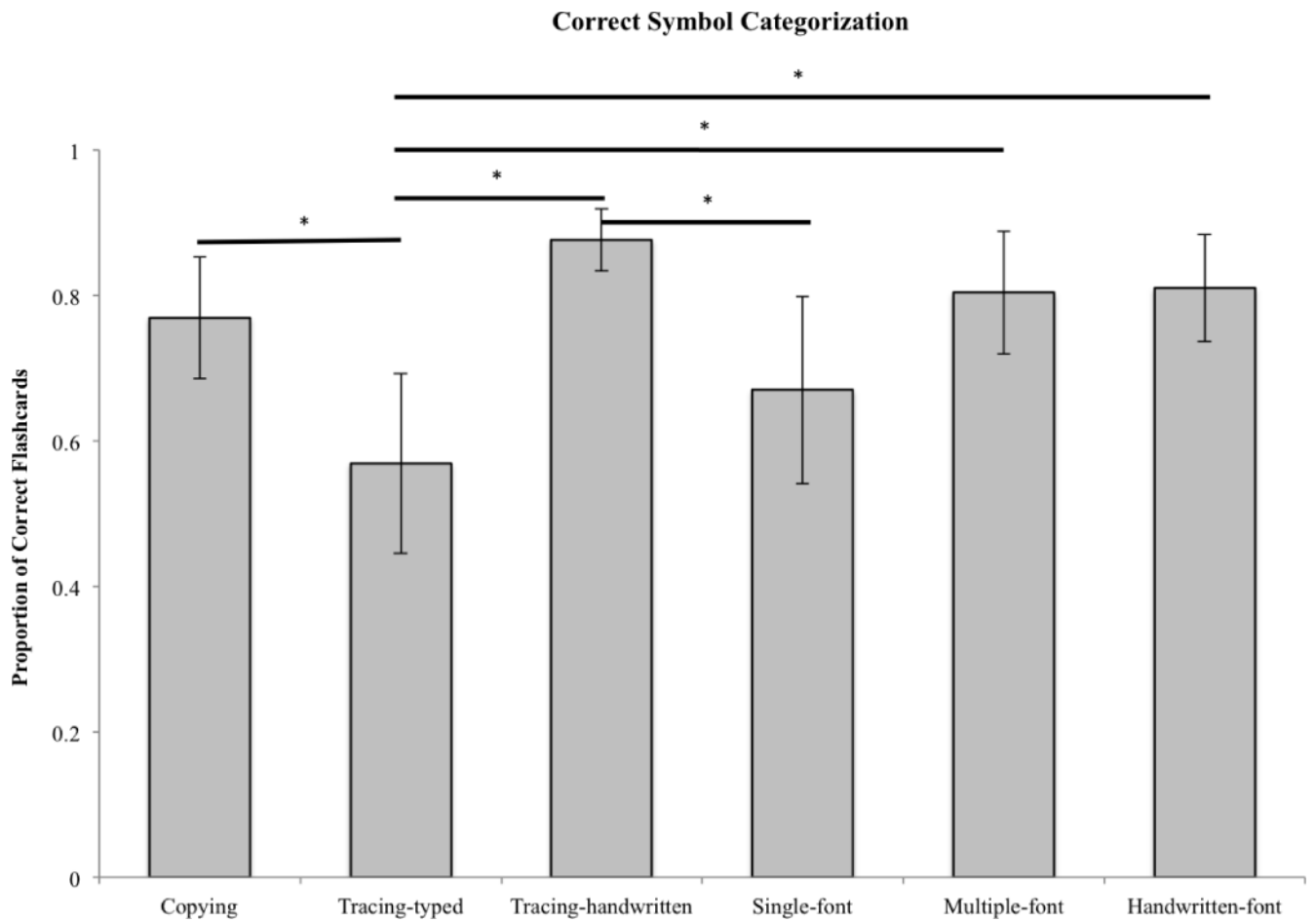
**Figure 5.**

Proportion correct (selection of the upright, learned symbol across all trials) for the Initial and Final 4AFC task across conditions. Significant improvement in symbol recognition for all conditions post card-sorting except Tracing-handwritten and Handwritten-font.

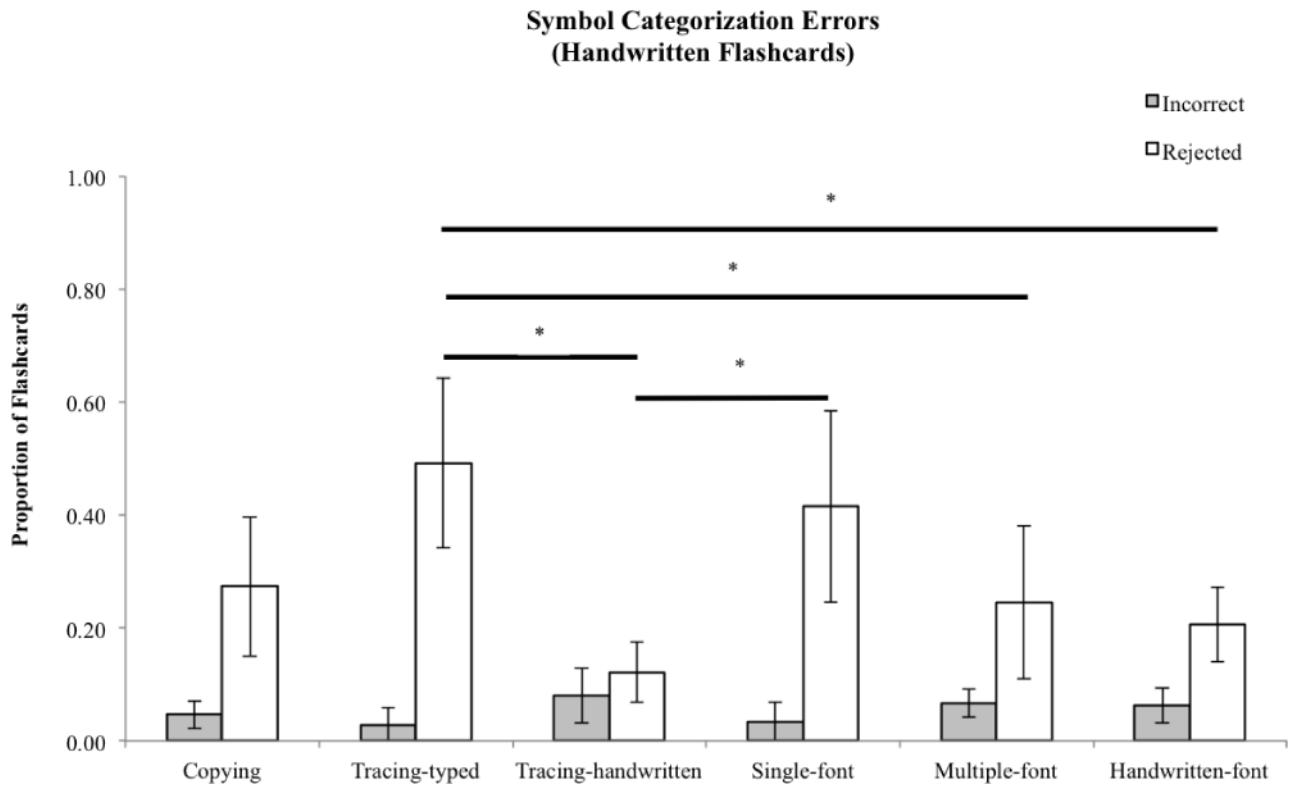
## Symbol Recognition Errors (4-AFC tasks)



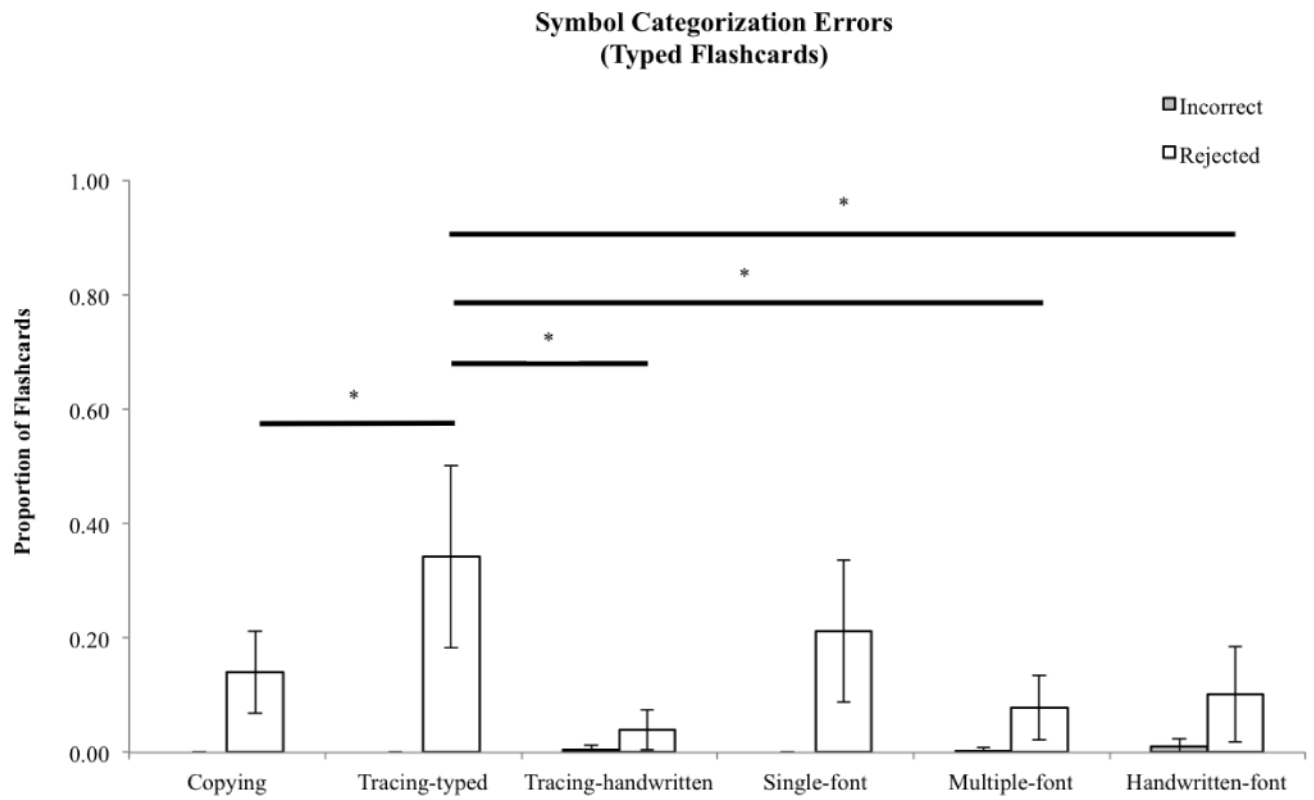
**Figure 6.** Recognition errors produced in the Initial and Final 4AFC tasks. Majority of errors involved participants selecting the misoriented symbols.



**Figure 7.** Differences in correct categorization across training conditions in the card-sorting task (combined typed and handwritten flashcards). Tracing-typed and single-font conditions were least successful at correctly categorizing variable symbol examples.

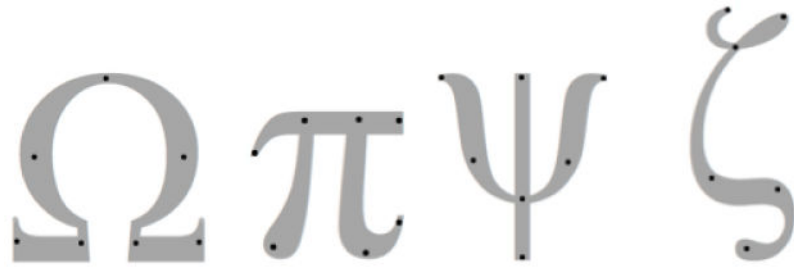


**Figure 8a.** Categorization errors across conditions for handwritten symbol examples. Tracing-typed and single-font conditions made the most categorization errors.



**Figure 8b.** Categorization errors across conditions for typed symbol examples. Tracing-typed and single-font conditions made the most categorization errors.





**Figure 9a.**

Anchor points used to measure variability in formation of symbols produced by the Copying and Tracing-typed learning conditions. Anchor points were used for post-processing data analyses only.



**Figure 9b.** Anchor points used to measure variability in formation of symbols produced by the Tracing-handwritten condition. Anchor points were used for post-processing data analyses only.

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