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The impact of handwriting and typing practice in children's letter and word learning: Implications for literacy development

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ABSTRACT

Recent research has revealed that the substitution of handwriting practice for typing may hinder the initial steps of reading development. Two hypotheses for the detrimental effect of typing are (a) reduced graphomotor activity and (b) reduced variability in the visual letter forms. However, previous studies were mostly limited to letter learning and primarily employed the visual identification of letters as a learning index. The current experiment investigated the impact of graphomotor action and output variability in letter and word learning using a variety of tasks. A total of 50 prereaders learned nine letters and 16 pseudowords made up of these letters across four learning conditions: copying the letters/words by hand, tracing the letters/words, typing the letters/words on a computer with several fonts, and typing with a single font. Posttest tasks included naming, writing, and visual identification of the trained letters and words. Results showed that children in the handwriting groups (i.e., trained through hand-copying or tracing) achieved higher accuracy across all posttest tasks compared with those in the typing groups. These outcomes illustrate the importance of handwriting experience in learning alphabetic and orthographic representations, favoring the graphomotor hypothesis. Thus,

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educators should be cautious about replacing pencil and paper with digital devices during the period of children's reading acquisition.

Introduction

Reading is critical for children's linguistic, communicative, socioemotional, and cognitive development (Kozak & Recchia, 2019) and serves as a cornerstone of future academic success (Whitten et al., 2019). Furthermore, reading proficiency is associated with increased school engagement, higher self-esteem, and greater confidence in academic skills (Torppa et al., 2020; Vasalampi et al., 2023). Consequently, the acquisition of reading skills and their enhancement through effective classroom practices are pivotal subjects within educational psychology (Caravolas et al., 2019; van Bergen et al., 2021).

The recent massive burst of digital media in the classroom has raised interest in clarifying whether the displacement of pencil and paper with typing in tablets or computers can alter the reading acquisition process. Although some studies warn about the adverse effects of this irruption on both general learning (Genlott & Grönlund, 2013) and reading comprehension (Delgado et al., 2018), reading and writing on tablets and computers continues to displace manual reading and writing at increasingly younger ages (Arndt, 2016; Malpique et al., 2024). Although a preventive view advocates limiting the use of these devices in the classroom at an early age, the question of how the hand versus digital experience with written word forms affects the reading acquisition process in preliterate children has not been explored in depth.

There is a broad consensus in the literature about two essential components of the reading acquisition process: alphabetic and orthographic knowledge (Torppa et al., 2016; Treiman, 2006). On the one hand, alphabetic knowledge involves learning the shape of letters and their associations with the corresponding sounds. This knowledge, which is an important predictor of later reading accuracy, is acquired in early childhood through play, naming, and letter writing (Zugarramurdi et al., 2022). Specifically, knowledge of letter forms and their sounds facilitates the association of letters with sounds during decoding (Wang et al., 2014), improves the identification of letters within words, and supports the accurate construction of orthographic word forms (Tucker et al., 2016). On the other hand, orthographic knowledge implies mastery of the specific combinations of letters that constitute words (Conrad et al., 2019, 2023). Knowledge of a word's orthographic properties, such as specific letter combinations and letter positions, develops progressively through print exposure in early childhood (Gómez et al., 2021; Mano & Kloos, 2018) and is a strong predictor of automatic and fluent reading in primary school (Deacon et al., 2019). A number of studies have shown that both decoding exercises (e.g., identifying letters and translating them into phonemes in a serial fashion) and manual writing exercises (e.g., identifying the phonemes that make up a word and translating them into their graphic representations) (Bosse et al., 2014; Shahar-Yames & Share, 2008) favor the development of orthographic knowledge because that both activities facilitate visual processing of the sequences of letters and sounds within words.

Within this general framework, handwriting practice has been identified as a key exercise supporting the acquisition of alphabetic and orthographic knowledge in the prereading stage given that it involves the precise reproduction of letter forms through perceptual–motor activity (Ray et al., 2022). The underlying rationale is that the tactile and motor experiences associated with handwriting play a critical role in embedding alphabetic and orthographic knowledge within the brain's learning mechanisms (Longcamp et al., 2005, 2008). Consequently, the shift from handwriting to typing in educational settings may negatively affect the literacy learning process, potentially hindering the development of reading and writing skills. Indeed, previous research highlights concerns that typing, compared with handwriting, may disrupt key cognitive processes essential for consolidating letter representations within neural pathways (James, 2017; Mangen & Balsvik, 2016; Seyll et al., 2020). In the following sections, we briefly review the literature and main models before introducing the experiment.

Handwriting and typing: Implications for letter learning

Most studies examining the relationship between handwriting and reading acquisition in childhood have focused on letter learning. A seminal study by Longcamp et al. (2005) involved a 3-week intervention with children aged 3 to 5 years, during which they learned 12 capital letters. Half of the children learned the letters through hand-copying, and the other half learned them by typing on a keyboard. In a posttest letter identification task, in which the children needed to select the target letter from four presented items (i.e., the target letter and three foils), those in the hand-copying training group showed a higher identification rate than those in the typing training group. Longcamp et al. (2005) suggested that hand-copying facilitates the construction of accurate letter representations because writing by hand involves movements that fully define the letter shapes, helping to build an internal model of the letter forms. This graphomotor hypothesis posits that the unique correspondence between the perceived letter and the movement used to write it contributes to greater accuracy in learning to read and write through handwriting compared with typing. When children type, a cognitive map of the keyboard must be constructed. However, in this case, there is no specific relationship between the visual shape of the letter and the movement required to produce it, which hinders the construction of accurate mental representations of letters (Mangen & Velay, 2010).

Subsequent studies have supported this view, replicating the basic findings with children of the same age who underwent digit training (Zemlock et al., 2018) and with adults who underwent symbol training under identical hand-copying and typing learning conditions (Longcamp et al., 2008). In addition, functional magnetic resonance imaging (fMRI) data have revealed overlapping neural activations during the visual processing of symbols learned through hand-copying and actual letters of the alphabet (Longcamp et al., 2008). In contrast, characters learned through keyboard typing might not engage neural pathways shared with letter processing, which has been attributed to the absence of a graphomotor component during learning. This specific contribution of handwriting to letter learning, initially documented with the Roman alphabet, has also been observed in other writing systems, including alphabetic scripts such as Arabic (Wiley & Rapp, 2021) and logographic scripts such as Chinese (Hsiung et al., 2017). Overall, these findings reinforce the notion that the activation and identification of mental representations of letters depend, to some extent, on the experience of how they are written.

However, the story may be more complex given that hand-copying letters is necessarily accompanied by some variability in the visual letter forms, which in turn could lead to the emergence of more stable letter representations. James and Engelhardt (2012) examined this issue by testing the impact of different types of writing experience on the neural activity of a sample of prereading children aged 4 and 5 years. These children were trained on a set of letters by hand-copying and another set of letters by tracing over dots. In an fMRI study, the authors analyzed brain activation patterns during a posttest letter identification task. They found that the perception of letters trained through hand-copying engaged brain regions associated with letter processing (inferior frontal gyrus, posterior parietal cortex, and left fusiform gyrus) to a greater extent than the perception of letters trained through tracing. This finding not only supports the central role of handwriting in letter learning but also suggests that the *variability of perceptual instances* generated by hand movements could be an additional explanatory mechanism for the effects observed in previous studies comparing handwriting and typing conditions.

To directly test the *variability hypothesis*, Li and James (2016) trained 5-year-old children on four Greek symbols that were unfamiliar to them in six learning conditions. Three of them involved visuomotor learning (hand-copying symbols, tracing symbols in Times New Roman, and tracing handwritten symbols), and three involved strictly visual learning (visualizing handwritten symbols, visualizing symbols written in Times New Roman, and visualizing symbols written in four different typefaces). A letter identification posttest revealed that participants who were trained in the visuomotor and visual conditions with less variability (e.g., tracing or visualizing Times New Roman symbols) made more identification errors than those who learned under greater perceptual variability conditions (e.g., tracing handwritten symbols, visualizing handwritten symbols, or visualizing symbols in different typefaces). These findings support the hypothesis that perceptual variability is another mechanism through which handwriting favors letter learning given that it might facilitate the extraction of invariant properties within the variations of written letters (i.e., leading to letter representations that are more resilient to variations; see Grainger, 2018). This may explain the higher letter recognition accuracy observed in the hand-copying condition compared with the production of more uniform letter copies through typing or tracing.

Although the above-cited studies are undoubtedly valuable in illuminating the best methods for letter learning in prereaders, there are two important caveats. First, they only employed visual identification of letters as an index of learning. However, identification tasks might not fully capture alphabetic learning—the ability to map letters to sounds—which is crucial for learning to read and spell. Letter naming and letter writing tasks may be necessary to obtain the whole picture. Second, the scope was limited to alphabetic learning, which does not allow us to determine whether the reported results can be generalized to the learning of orthographic representations.

Impact of handwriting practice on orthographic learning

Despite the importance of orthographic processes in reading, the relationship between handwriting and the learning of orthographic word representations has received little attention in the literature. Although in principle the same rationale for alphabetic learning could be applied to orthographic learning, it remains unclear whether the effects observed in alphabetic learning also extend to orthographic learning. The limited existing studies with children provide insufficient evidence to draw clear conclusions. For instance, Ouellette and Tims (2014) found that second-grade children showed similar recognition and spelling rates for nonwords trained by hand-copying or typing, with learning being highly dependent on children's prior typing expertise. This may be because children at this age have already developed certain orthographic knowledge through their handwriting experience (encoding retrieval match effect). However, as shown below, the few studies with prereaders have also yielded inconsistent results.

On the one hand, Kiefer et al. (2015) reported higher word reading and writing rates in 5-year-old German prereaders trained in letters of their alphabet by hand-copying compared with those trained in the same letters by typing. On the other hand, Mayer et al. (2020) trained prereaders aged 4 to 6 years to learn letters and words in German under three conditions: hand-copying, stylus writing on a tablet, and typing on a keyboard. The training phase included associating letter forms with sounds and letter strings with word pronunciations. Posttest tasks assessed letter identification, writing trained letters to dictation, word naming, and writing trained words to dictation. Mayer et al. (2020) found that hand-copying generated a higher accuracy rate in letter identification, replicating previous findings (Longcamp et al., 2005). However, unlike Kiefer et al. (2015), they did not find differences between hand-copying and typing conditions in word writing and naming measures.

Interestingly, Wiley and Rapp (2021) examined this issue with adult native speakers of English who were learning Arabic. Participants were divided into three learning groups: hand-copying, keyboard typing, and visual learning (i.e., observing and memorizing the novel letters without motor involvement). They were trained over several sessions by being exposed to letters and short words composed of Arabic symbols. Wiley and Rapp found that participants in the hand-copying training group were more accurate in letter identification and letter naming than participants trained in the other conditions (typing and visual), supporting the graphomotor hypothesis. Subsequently, they evaluated whether this knowledge generalized to the recognition of word representations using a same–different task. Their findings showed that participants in the hand-copying group were better at detecting different pairs, regardless of whether the typography differed from the trained one, thereby supporting the variability hypothesis. Importantly, this benefit was also observed in other untrained tasks, such as writing words to dictation. However, Wiley and Rapp (2021) acknowledged that their findings might not necessarily reflect how the learning process occurs in childhood: Adults already have extensive alphabetic experience and high orthographic knowledge in their language, which may facilitate both the association of new letters to sounds and the use of strategies to memorize orthographic patterns.

The current study

This study addressed the limitations of previous research. It examined to what extent graphomotor action and variability contribute to the process of learning accurate letter and orthographic representations in prereaders by comparing two handwriting training conditions and two typing training conditions across a series of tasks.

The primary goal was to determine to what extent the explanatory mechanism of the benefit of handwriting over keyboard typing for alphabetic and orthographic learning can be attributed to the graphomotor action, the variability generated during writing, or a combination of both. On the one hand, reproducing novel letters by hand may facilitate letter learning more effectively than typing the letters (*graphomotor hypothesis;* Longcamp et al., 2005), and for orthographic learning the action involved in writing a letter string may promote the retention of the specific sequence of letters that make up each word better than keyboard typing. On the other hand, generating variable instances of letters and letter strings in high-variability conditions (hand-copying and typing with a variable font) may enhance the retention of letters and orthographic sequences (*variability hypothesis;* Li & James, 2016) compared with conditions in which children generate stable instances of letters and letter strings (tracing and typing in a single font).

In the current experiment, children in the last year of kindergarten were trained to learn unfamiliar letters—taken from the Georgian and Armenian alphabets—and letter strings across four training conditions that manipulated graphomotor action and variability: (a) hand-copying [G +] resulting in variable exemplars [V +], (b) tracing [G +] producing approximately uniform exemplars [V –], (3) typing [G-] with varying fonts [V +], and (4) typing [G –] with a single font [V –].

The experiment consisted of two phases; the first phase focused on letter learning, and the second one focused on learning novel words constructed with those letters. Letters and words were presented with their corresponding pronunciations, simulating the reading acquisition process. We employed a series of posttest tasks to measure alphabetic and orthographic learning. Alphabetic learning tasks included (a) visual identification of letters (measuring the ability to visually recall the trained letter shape), (b) letter naming (mapping the visual letter shape with its corresponding sound), and (c) letter writing (recalling the letter shape from the sound). Orthographic tasks included (a) word identification (visually discriminating the trained word from a similar letter string), (b) word naming (applying letter–sound association rules essential for decoding), and (c) word writing (retrieving the orthographic form from memory when listening to the word and mapping each sound to its corresponding letter in sequence).

Method

Data availability

All stimuli, data, analysis scripts, and outputs are available on the Open Science Framework (OSF) (https://osf.io/m2jh8/?view_only=954f06d3352a48d5ab41514e75aecac2).

Participants

A total of 50 children in the last year of kindergarten (mean age = 5.4 years; 22 girls) participated in this experiment with the informed consent of their parents. The children were randomly assigned to one of four training subgroups designed to examine two main comparisons: (a) handwriting versus typing and (b) high versus low variability. The handwriting subgroups included hand-copying (n = 13) and tracing (n = 13), and the typing subgroups included typing with varying fonts (n = 12) and typing with a single font (n = 12). High-variability conditions included hand-copying and typing with varying fonts, whereas low-variability conditions included tracing and typing with a single font.

A power analysis for subgroup contrasts (Westland, 2010) indicated that the optimal sample size to achieve a statistical power of.80 with an alpha of.05 and a medium effect size (d = .50), was 50. This statistical power was sufficient for the primary contrasts of interest: handwriting versus typing and high versus low variability. The sample was selected from a school in an urban area of the Basque Country in Spain. The children met the following inclusion criteria: (a) being enrolled in the last year of kindergarten, (b) absence of neuropsychiatric disorder or sensory problems, and (c) no history of special education services or reading or language therapy. All participants were native speakers of Spanish, a transparent language in which letter–sound correspondences are univocal.

The study was conducted under the guidelines of the ethical committee of the University of the Basque Country, project approval reference M10_2020_060 and 1894511_Universitat de Valéncia.

Materials and design

Control measures

Knowledge of Spanish letters. Participants were shown 20 letters of the Spanish alphabet in random order and asked to pronounce the corresponding sound of each letter. Letters were presented in uppercase and sans-serif typeface to ensure consistency across trials. The raw number of hits was used as a measure of letter knowledge. Participants needed to correctly name at least 70% of the letters to participate in the study. This criterion was employed to ensure that children could map sounds to letters, which is a fundamental skill for learning new symbol categories (see Li & James, 2016).

Verbal working memory. This ability was assessed with the backward digit task of the Wechsler Intelligence Scale for Children–Fourth Edition (Wechsler, 2003). Seven series of two trials each were presented. Each series incorporated an additional digit, starting from a two-digit trial. The experimenter presented the digits verbally, the time between items was set to 1 s, and the time between trials was set to 10 s. The child was asked to repeat each trial aloud. The children's verbal responses were recorded to facilitate later transcription and analysis. The highest number of well-remembered digits was taken to indicate verbal memory span.

Fine motor skills. Two tasks from the Movement Assessment Battery for Children-2 (Henderson et al., 2007) were used to assess this ability. Specifically, participants performed the Bead Threading and Drawing the Trace tasks related to the Manual Dexterity dimension. In the Bead Threading task, each participant had 1 min to thread as many beads as possible onto a string. The experimenter would start the test and signal completion when the time limit was reached. The Draw the Trace task consisted of tracing with a pencil a winding path without going outside the delimited edges. Participants were instructed to avoid lifting the pencil from the sheet once the tracing started. The number of strokes made to finish the course without leaving it was established as an indicator of tracing quality. Interrater reliability was 82.3% (Cohen's κ = .726).

Stimuli

Letters. The stimuli consisted of nine unfamiliar letters drawn from the Armenian and Georgian alphabets, which were novel for Spanish readers; three were trained as vowels ք, Ձ, Դ (which were associated with the sounds /a/, /o/, and /e/, respectively), and six were trained as consonants ძ, Ե, Փ, Ծ, Կ, Թ (which were associated with the sounds /l/, /f/, /n/, /t/, /s/, and /p/, respectively). In all cases, the novel letters had a regular and univocal association with a sound in Spanish (e.g., /k/ can be represented by both "k" and "c"). All the materials for the test tasks were the same in the four learning conditions: manual copying from a Tahoma model (graphomotor activity + variability +); manual tracing on a Tahoma model (graphomotor activity + variability –); keyboard typed copying with two fonts, Tahoma and manual style (graphomotor activity – variability +); and keyboard typed copying with a Tahoma font (graphomotor activity – variability –). The computer fonts for the symbols were constructed using the Caligraphy program, which allows a key to be assigned to a new imported font, thereby creating a keyboard for the novel orthography.

Words. With the above letters, 16 two-syllable words with consonant–vowel (CV) structure (i.e., the more common in Spanish) were constructed. CV (ԾՋႾጉ, ძጉዓՋ, ዋՋፆቶ, ԾቶႾՋ, ዋጉዓቶ, ძቶፆጉ, ძՋዓጉ, ዋጉፆՋ, ԾՋႾቶ, ძቶዓՋ, ԾጉႾቶ, ዋቶፆጉ, ძጉዓቶ, ዋቶႾՋ, ԾጉፆՋ, ძՋႾጉ) (tofe, leso, nopa, tafo, nesa, lape, lose, nepo, tofa, laso, tefa, nape, lesa, nafo, tepo, and lofe, respectively). The words were constructed following a certain positional regularity of the letters so that the consonants Ծ, ძ, ዋ were always placed in the first position and the consonants Ⴞ, ዓ, ፆ were always placed in the third position.

Procedure

The training and testing were conducted individually in a classroom within the same educational center. Each participant attended three 45-min sessions held on 3 consecutive days. The first session tested prereading skills (control measures). The second and third sessions were devoted to novel letter and novel word training, respectively, and their corresponding posttest tasks: letter naming, letter writing, and letter identification in the second session after letter training and novel word reading, writing, and orthographic choice in the third session after novel word training. Each training session included two learning blocks before the posttest tasks (see Fig. 1). Each letter learning block consisted of 6 trials (letter presentation + reproducing), for a total of 12 trials, and each word learning block consisted of 3 trials (word presentation + reproducing), for a total of 6 trials. The reason for dividing the session into two blocks was twofold: to provide a break for the child and to monitor the child's progress by asking the child to name the trained items as presented in each condition (letter on paper or letter on computer screen).

Because the novel alphabet was fully transparent and there was no irregularity or inconsistency, the experimenter pronounced a letter sound corresponding to each novel letter during the visual presentation (Torppa et al., 2016). This was essential to facilitate generalization to word reading and writing, which requires knowledge of grapheme–phoneme mappings rather than letter names. During each session, children were asked to learn the shapes and sounds of the letters or words presented and were informed that they would be tested on this knowledge afterward. Participants were ran-

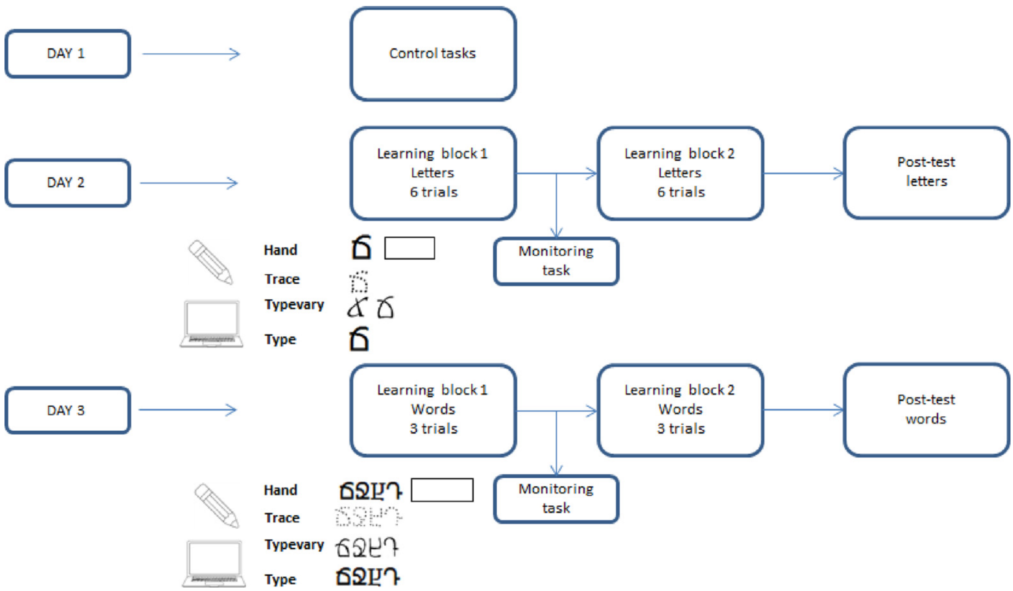


Fig. 1. Training and testing protocol in the second session (letters) and the third session (words). The training tasks were constructed to build knowledge of individual novel letter and words in different conditions. The posttest tasks probed knowledge of the trained letters and words (naming, writing, and identification).

domly assigned to one of the four learning conditions: hand-copying, tracing, typing with a single font, or typing with varying fonts. The task instructions for each learning condition are summarized below. To ensure comparability among conditions, the similarity between the different learning conditions was maximized by ensuring that all of them involved the same exposure to the stimuli for a similar duration.

Novel letter training

In the novel letter training phase, each participant was asked to observe the novel letter shape, listen to the sound associated with that letter, repeat the sound, and reproduce the letter. The reference models of the novel letters were presented one by one either on a sheet of paper or on a computer screen. For each letter, the visual presentation was shown first, followed by the experimenter pronouncing the corresponding sound. Each letter training involved 12 trials (letter presentation + repro duction) for each novel letter under the learning condition assigned to the participant. Letter training was divided into two blocks with 6 trials each. To ensure equivalence across the different learning conditions, all participants produced the same number of copies of each letter and pronounced its sound only once per letter presentation. Given that children needed to learn nine letters and each letter was presented 12 times, the total number of trials/copies in the letter learning session was 108. Each training block was designed to be completed in around 10 min. Both blocks were spaced apart by a novel letter naming test to monitor the child's progress in the naming of the trained letters in each condition.

Hand-copying. Children were given a booklet of blank sheets of paper, each with the printed reference model of a novel letter at the top in Tahoma font. Each novel letter to be trained was displayed individually. The experimenter presented the letters in random order and named each one aloud. The child was then asked to repeat the sound once and copy the letter into a designated box at the bottom of the sheet.

Tracing. The procedure was the same as in the hand-copying condition. However, instead of reproducing the novel letters onto blank sheets of paper, participants were required to repeat the sound once and trace each novel letter over models outlined with small dots. In this condition, the model remained consistent for each letter across all 12 trials. This consistency minimized variability while preserving the graphomotor component.

Typing with a single font. Participants observed each novel letter individually on a computer screen in Tahoma font while the experimenter pronounced the letter sound aloud. The child was asked to repeat the sound and then find and press the corresponding key on a specially designed keyboard that matched the shape displayed on the screen. When the key was pressed, the shape produced by the participant disappeared, and after 10 s a blank screen was replaced with a new novel letter.

Typing with varying fonts. The procedure was the same as the previous condition except that half of the time the shape on the computer screen appeared in Tahoma font (as in the reference model), and the other half of the time it appeared in a digitized font that simulated handwritten letters.

Novel word training

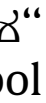
Novel word training took place after completing the letter training and posttest measures. During this training, each participant was required to view 16 pseudowords (composed of the trained letters from the previous session), listen to their pronunciations, and subsequently transcribe them under the assigned condition following the same procedure employed in the letter training session. The training session consisted of 6 trials divided into two blocks, with each block involving the child seeing and writing every novel word six times, resulting in a total of 96 transcriptions. The two blocks were spaced apart by a monitoring task in which children needed to name the trained pseudowords. This task served as an indicator of the learning progress for each child in each condition before continuing with the training session. Each block was designed to be completed in approximately 20 min.

Posttest tasks

Letter training posttest tasks

Novel letter naming task. The same nine symbols used in the letter training phase were presented in the naming task in random order. The participant viewed each item individually on a paper index card and was asked to produce the associated sound. Each correctly named letter contributed 1 point to the total score. Therefore, the maximum score achievable on this test was 9 points for correctly identifying all the letters, whereas the minimum score was 0 points if none of the letters was correctly named. This measure was recorded twice during the investigation: once between the two letter training blocks (monitoring test in the second session) and a second one at the end of the second session after the training was completed. Interrater reliability was 99.6% (Cohen's κ = .982). The posttest task explored the degree of short-term consolidation of the letters after the whole learning session.

Letter writing task. Children heard the sound of each of the nine letters in random order and needed to draw the corresponding letter with a pencil on a 6 × 4-cm blank index card. After completing the two training blocks, this task was performed at the end of the second session. A correct score was given if the drawing reflected the original letter shape (1 = letter shape fully defined and correct, 0 = missing defining elements or major error). Interrater reliability was 93.5% (Cohen's κ = .893). The dependent measure consisted of the total number of correct answers (sum of correctly written letters; maximum score per participant = 9, minimum score per participant = 0).

Letter identification task. The four-alternative forced-choice (4AFC) task assessed letter identification (Li & James, 2016). This visual recognition test required participants to point to the trained letter among four options. We employed the same design as Li and James (2016) so that the target "" was presented with three distractors: a rotated version of the trained letter (), an untrained symbol (λ), and a geometric figure (□). This task assesses not only the ability to categorize the newly learned letters but also the ability to distinguish them from other symbols that are visually similar—or the same but with different spatial orientations.

Each trial presented a random novel letter with its three distractors forming a square, and the child needed to point to the one he or she identified as one of the newly learned letters. The test consisted of 72 trials divided into two blocks, spaced by a 15-s rest period. The position of the target letter in the square varied orthogonally across trials, ensuring that each target letter appeared eight times in total during the test, twice in each position (top left, top right, bottom left, and bottom right). In half of the trials the target letters and distractors were presented in Tahoma font, and in the other half they were presented in a font simulating handwritten letters and symbols. The test was implemented on a computer using DMDX (Forster & Forster, 2003) to ensure a uniform presentation of the stimuli. The child had 5 s to point to one of the four options on each trial. Failure to answer within this interval automatically advanced the presentation to the subsequent trial. The hit rate was used as a measure of categorization. A correct response was given if the participant correctly identified the target (maximum score per participant = 72, minimum score per participant = 0).

Word training posttest tasks

Novel word reading task. The same 16 pseudowords used in the word training phase were presented in the reading task. The words were displayed on paper in random order, and participants were asked to attempt to pronounce them. A correct response was recorded only if the participant correctly decoded the full symbol string. An error in any sound was counted as an error in decoding the word (maximum score per participant = 16, minimum score per participant = 0). Interrater reliability was 92.2% (Cohen's κ = .896). This measure was recorded twice: once between learning blocks in the middle of the third session as a learning monitoring test and once at the end of the third session as a posttest measure.

Novel word writing task. To shorten the task, 4 of the 16 novel words learned during training were selected, ensuring that they contained all the letters and sounds learned. The goal was to produce them as accurately as possible on blank 16 × 4-cm index cards. All participants, regardless of their training condition, were required to perform the task through handwriting. This task was performed once after completing the word training blocks. A conservative measure for accuracy was employed (correctly written complete pseudoword = 1, word written with one or more errors = 0). Therefore, the maximum score for this measure per participant was 4 points, achieved by correctly writing all the letter strings without any errors, and the minimum score was 0. An external coder blind to the study coded the word writing data based on the mentioned criteria. Interrater reliability was calculated for accuracy ratings. The percentage of agreement between the experimenter and external coding was 91.6% (Cohen's κ = .867).

Orthographic identification task. This task was designed to evaluate whether word recognition accuracy differed as a function of learning condition. On each trial, the child was presented with two items, one to the right and one to the left of the center of the screen, and was asked to identify as quickly as possible which one was the familiar trained item. The child made his or her choice by pressing one of two keys assigned to the words on the left and right. The task consisted of 32 trials distributed across two blocks. The child had 11 s to respond on each trial before advancing to the next one. The 16 trained items were presented twice: once with a distractor that differed from the target by the substitution of a consonant (ԾՋᄔጉ–ԾՋዋጉ) and once with a distractor that differed by the transposition of consonants (ԾՋᄔጉ–ᄔՋԾጉ). This manipulation aimed to assess the degree of completeness in encoding letter identity and position (Chetail, 2017). Trials were randomly distributed between the two blocks (16 items per block), and the location of the distractor—left or right—was counterbalanced across presentations. In addition, half of the trials contained items written in Tahoma font, and the other half simulated handwriting. Accuracy in this task was assessed as the percentage of correctly identified trained pseudowords. The tests were implemented on a computer using DMDX (Forster & Forster, 2003) to ensure a uniform presentation of the stimuli. Accuracy ratings indicated the ability to discriminate the familiar item from the distractor (i.e., the ability to recognize and recall the correct spelling of words).

Data analysis

The accuracy data for naming, writing, and identification of letters and words in each post-training task were used as the dependent variables. For all analyses, the fixed factors were graphomotor action (handwriting vs. typing; encoded as – 0.5 and 0.5, respectively) and variability output (high vs. low; encoded as – 0.5 and 0.5, respectively), using contrast coding to center the factors. Inferential analyses were conducted using Bayesian linear mixed-effects models implemented with the "brms" package in R (Bürkner, 2017; R Core Team, 2023). Accuracy was modeled with the Bernoulli function (for each trial, 1 = correct, 0 = incorrect). We used the default non-informative priors from brms (see Scholz & Bürkner, 2023). For all models, we applied the maximal random-effects structure permitted by the design (see Barr et al., 2013, for arguments supporting this choice). The random factors included intercepts for participants and items as well as slopes for the interaction between graphomotor action and variability output for items. Given that participants were assigned to different levels of graphomotor action and variability output, random slopes for these factors by participant were not included. The syntax for each model was as follows: accuracy ~ Graphomotor Action * Variability Output + (1 | participant) + (1 + Graphomotor Action * Variability Output | item).

For the fits of each model, we used four chains, each with 5000 iterations (including 1000 warm-up iterations). The output included the estimate, estimation error, and 95% credible interval (CrI) for each fixed effect. Estimates with 95% CrIs that did not cross zero were interpreted as evidence of an effect (see Dänbock et al., 2023, for a similar procedure). We chose to examine 95% CrIs instead of Bayes factors because CrIs provide a clearer representation of parameter uncertainty, particularly in small samples, and are less sensitive to prior specifications. It is worth noting that brms (Bürkner, 2017) does not support the computation of Bayes factors with the default priors.

Results

The descriptive data for the control tasks in the sample are presented in Table 1. No significant differences between groups were found in any of the control measures. This step was necessary to ensure that no other factors could account for the differences observed between groups, confirming that any variations in posttest accuracy for alphabetic and orthographic tasks could be attributable to the training condition.

The descriptive data for the monitoring and posttest tasks in the sample are presented in Table 2. In the following section, we summarize the results of each posttest task for assessing letter and word knowledge.

For all Bayesian linear mixed-effects models, the four chains converged successfully ($\hat{R}$s = 1.00 in all cases; this is an index of model chain convergence, where 1 indicates perfect mixing). For completeness, parallel analyses using frequentist generalized linear mixed-effects models—with intercepts for participants and items—using the "lme4" package (Bates et al., 2015) revealed essentially the same pattern of findings as reported here; these analyses are in the OSF link (https://osf.io/m2jh8/?view_only=954f06d3352a48d5ab41514e75aecac2). The only exception was that the frequentist analyses detected an effect of variability in the letter naming task ($z = -2.427$, $p = .015$), whereas the 95% credible interval in the Bayesian analyses overlapped with zero (95% CrI [−3.96, −0.36]).

Posttest tasks related to alphabetic knowledge

As a measure of the predictive accuracy of the models, we employed the leave-one-out information criterion (LOO-IC), where lower values indicate better fit. The LOO-IC for the letter naming model was 316.2, with 98.6% of observations showing stable predictions; for the letter categorization model it was 1564.8, with all observations demonstrating excellent stability; and for the letter writing model it was 470.6, with 99.8% of observations showing reliable predictions. The Bayesian R^2 for the letter naming model was.29 (95% CrI [.20,.37]), for the letter categorization model it was.10 (95% CrI [.07,.13]), and for the letter writing model it was.39 (95% CrI [.33,.44]).

Letter naming

Handwriting-trained letters were named more accurately than typing-trained letters (92.3% vs.75.5% accuracy, respectively), $b = -3.02$, *estimation error* = 0.93, 95% CrI [−5.09, −1.41]. In addition, although letters trained in the high-variability groups were named more accurately than those in the low-variability groups (88% vs. 79.8%, respectively), the 95% CrI included zero, $b = -1.99$, *estimation error* = 0.92, 95% CrI [−3.96, −0.36]. More important, we found evidence of an interaction between graphomotor action and variability, $b = 3.33$, *estimation error* = 1.76, 95% CrI [0.21, 7.21]. Simple-effects tests on this interaction using the "emmeans" package (Lenth et al., 2020) showed that for the handwriting groups accuracy was higher in the hand-copying condition than in the tracing condition (99.1% vs. 85.5%, respectively), $b = 3.51$, 95% CrI [0.87, 6.99]. In contrast, we did not find an effect of variability for the typing groups (76.8% and 74.1% accuracy in the group typing with varying fonts

Table 1
Descriptive variables of the sample in control tasks: Raw measures.

	n	Mean age (years)	Letter knowledge	Verbal working memory	Fine motor skill	
					Trace	Balls
Experimental group			*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	
Hand-copying	13	5.5	16 (3.02)	3.40 (1.12)	2.31 (1.11)	8.15 (1.77)
Tracing	13	5.3	15 (4.87)	2.80 (1.09)	2.23 (0.83)	9.46 (2.57)
Typing with varying fonts	11	5.6	14 (4.73)	3.30 (1.50)	2.27 (1.19)	8.09 (1.58)
Typing with a single font	12	5.4	14 (4.02)	2.80 (1.36)	3.17 (1.70)	7.91 (2.39)
			$F(3, 48) = 2.73$, $p = .08$	$F(3, 48) = 1.14$, $p = .23$	$F(3, 48) = 1.59$, $p = .20$	$F(3, 48) = 1.90$, $p = .14$

Table 2
Descriptive variables (percentage accuracy values) of the sample during training (between-block monitoring) and posttest tasks.

	Letter monitoring	Letter naming	Letter writing	Letter identification	Word monitoring	Word naming	Word writing	Word identification
Experimental group	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)	*M* (*SD*)
Hand-copying	64.9 (0.5)	99.1 (0.1)	73.5 (0.4)	94.1 (0.2)	81.7 (0.5)	81.7 (0.3)	86.5 (0.3)	62.5 (0.4)
Tracing	50.4 (0.4)	85.4 (0.3)	55.5 (0.5)	91.8 (0.2)	62.1 (0.6)	62.1 (0.9)	51.9 (0.5)	60.5 (0.4)
Typing with varying fonts	26.2 (0.5)	76.7 (0.4)	30.3 (0.4)	92.4 (0.3)	39.7 (0.4)	39.7 (0.4)	11.3 (0.3)	45.0 (0.4)
Typing with a single font	25.0 (0.3)	74.1 (0.4)	25.0 (0.4)	89.0 (0.2)	35.9 (0.5)	35.9 (0.4)	4.1 (0.2)	51.0 (0.5)

vs. typing with a single font conditions, respectively), b = 0.32, 95% CrI [−1.28, 2.02] (see the left panel of Fig. 2 for the estimates of the parameters in the posterior distributions).

Letter writing

We found an overall effect of graphomotor action; letters trained in the handwriting groups were written with greater accuracy than letters trained in the typing groups (64.5% vs. 27.7% accuracy, respectively), b = −2.36, *estimation error* = 0.55, 95% CrI [−3.53, −1.34]. In addition, we did not obtain clear evidence that variability plays a role in the letter writing task, b = −0.79, *SE* = 0.54, 95% CrI [−1.88, 0.25], nor did we find evidence of an interaction between the two factors, b = 0.52, *SE* = 0.86, 95% CrI [−1.18, 2.21]. See the middle panel of Fig. 2 for parameter estimates from the posterior distributions.

Letter identification

All conditions performed similarly, close to a ceiling level (90%–93% accuracy), and we found no evidence of any effects (i.e., participants could identify the learned letters regardless of training con-

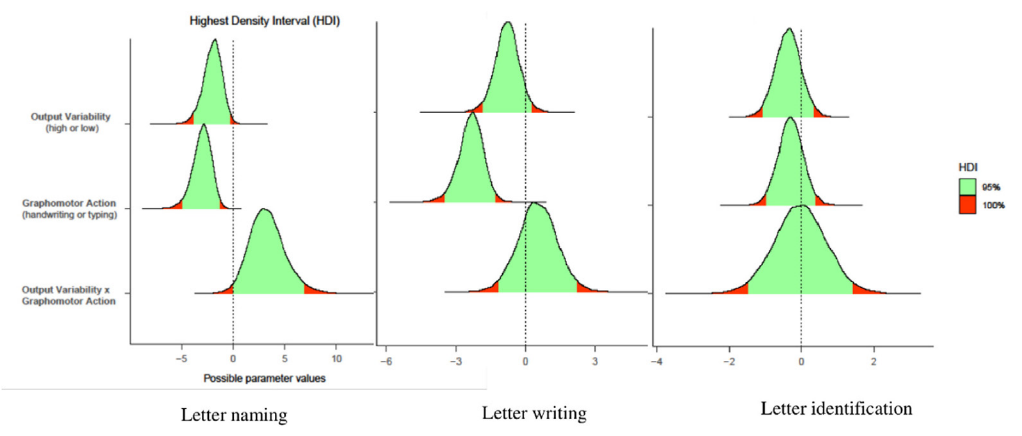


Fig. 2. Posterior highest density intervals (HDIs) of the parameters in the Bayesian linear mixed-effects analyses for the posttest tasks related to alphabetic knowledge. The left panel corresponds to the letter naming task, the middle panel to the letter writing task, and the right panel to the letter identification task. The area covered by the 95% credible Intervals is shown in green. An effect was interpreted as present when the credible interval of the parameter estimate did not include zero. (For interpretation of the reference to color in this figure legend, the reader is referred to the Web version of this article.). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ditions), all *b*s < 0.38. (see the right panel of Fig. 2 for the estimates of the parameters in the posterior distributions).

In sum, graphomotor training resulted in higher accuracy in both letter naming and letter writing tasks compared with typing. An interaction between graphomotor action and variability was observed only in the letter naming task. In contrast, no differences were found across training conditions in the letter identification task, where all groups performed at a similar near-ceiling level.

Posttest tasks related to orthographic knowledge

The LOO-IC for the word naming model was 647.5, with 99.6% of observations showing stable predictions; for the word identification model, all observations demonstrated excellent stability; and for the word writing model the LOO-IC was 78.3, with 77.5% of observations having stable predictions (note that this was likely due to the fact that accuracy in the word writing task was very low for the typing groups). The Bayesian R^2 values were.53 (95% CrI [.50,.57]),.07 (95% CrI [.04,.09]), and.86 (95% CrI [.80,.92]), respectively.

Word naming

Words trained in the handwriting groups were named more accurately than those trained in the typing groups (71.9% vs. 37.9% accuracy, respectively), $b = -2.96$, *estimation error* = 0.86, 95% CrI [−4.78, −1.37]. The numerical pattern showed that naming accuracy was higher for words trained in high-variability groups than in low-variability groups (60.8% vs. 49%, respectively). However, the estimate crossed zero, $b = -0.99$, *estimation error* = 0.82, 95% CrI [−2.63, 0.61]. We did not find any clear signs of interaction between graphomotor action and variability, $b = 1.36$, $SE = 1.65$, 95% CrI [−1.85, 4.64] (see the left panel of Fig. 3 for the estimates of the parameters in the posterior distributions).

Word writing

On average, words trained in the handwriting groups were written with much greater accuracy than words trained in the typing groups (69.2% vs. 7.8% accuracy, respectively), $b = -18.33$, *estimation error* = 7.55, 95% CrI [−37.14, −8.03]. In addition, although the numerical pattern showed that words

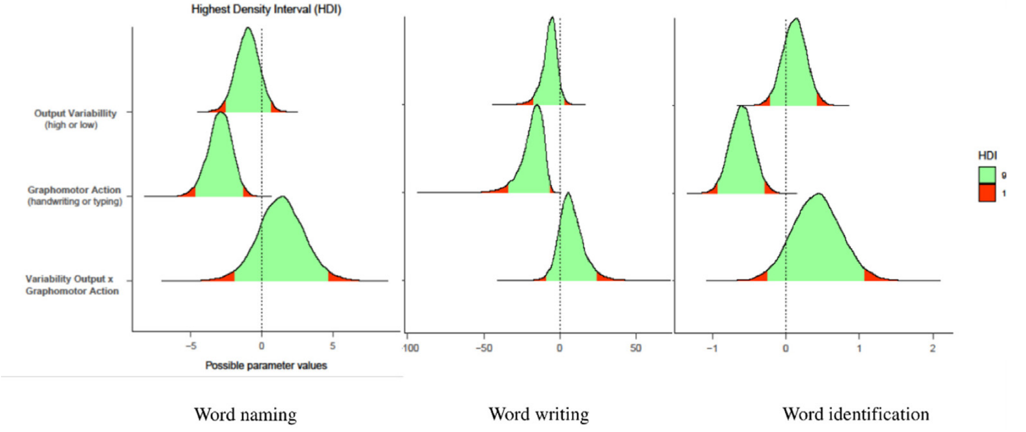


Fig. 3. Posterior highest density intervals (HDIs) of the parameters in the Bayesian linear mixed-effects analyses for the posttest tasks related to orthographic knowledge. The left panel corresponds to the word naming task, the middle panel to the word writing task, and the right panel to the word identification task. The area covered by the 95% credible Intervals is shown in green. An effect was interpreted as present when the credible interval of the parameter estimate did not include zero. (For interpretation of the reference to color in this figure legend, the reader is referred to the Web version of this article.). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

trained in high-variability groups were written more accurately than words trained in low-variability groups (49% vs. 28.1%, respectively), the estimate crossed zero, $b = -6.75$, *estimation error* = 5.16, 95% CrI [−18.74, 1.82]. Again, we did not find clear evidence of an interaction between the two factors, $b = 7.65$, *estimation error* = 8.40, 95% CrI [−6.71, 27.07]. See the middle panel of Fig. 3 for the estimates of the parameters in the posterior distributions.

Word identification

Children in the handwriting groups identified trained words more accurately than their peers in the typing groups (61.6% vs. 47.8% accuracy, respectively), $b = -0.60$, $SE = 0.16$, 95% CrI [−0.92, −0.28]. In addition, there was no evidence of an effect of variability; words trained in high-variability groups were identified with approximately the same accuracy as words trained in low-variability groups (53.3% vs. 56.1%, respectively), $b = 0.12$, $SE = 0.16$, 95% CrI [−0.21, 0.44]. Finally, we found no evidence of a two-way interaction, $b = 0.42$, $SE = 0.33$, 95% CrI [−0.30, 1.09]. See the right panel of Fig. 3 for the estimates of the parameters in the posterior distributions.

For the posttest tasks related to orthographic knowledge, graphomotor training resulted in significantly higher accuracy in word naming, writing, and identification compared with typing, with no substantial evidence of variability effects or interactions. This pattern suggests that graphomotor action plays a central role in the consolidation of orthographic knowledge.

Discussion

We designed an experiment to examine the extent to which graphomotor action and letter form variability contribute to the consolidation of alphabetic (letter-level) and orthographic (word-level) representations in the initial stages of reading development, thereby testing two distinct yet potentially complementary accounts. Graphomotor theories (Longcamp et al., 2005) propose that the motor actions involved in handwriting facilitate the integration of visual shapes with mental representations of letters and letter strings. Variability theories (Li & James, 2016) suggest that the perceptual variability of instances generated during writing enhances the consolidation of letters and letter strings. In the current experiment, 5-year-old children were trained on a set of novel letters and words through four different learning modalities. To test the graphomotor theory, two groups of participants were trained in handwriting (either by hand-copying or tracing letters with pencil and paper), and the other two groups were trained to type on a keyboard. To test the variability theory, two groups of participants were trained with variable exemplars (either by hand-copying letters or by typing letters in variable fonts), and the other two groups were exposed to exemplars with very limited variability (either tracing dot shapes or typing in a fixed font).

Results showed that graphomotor action (regardless of whether it involved hand-copying or tracing) enhanced learning outcomes in both alphabetic and orthographic posttest tasks, supporting the graphomotor hypothesis. Participants in the hand-copying and tracing groups achieved the highest accuracy scores in letter naming and letter writing posttest tasks. They were also more accurate in word naming, word writing, and word identification posttest tasks compared with the two typing groups. Notably, the typing groups demonstrated relatively low levels of accuracy, particularly in the word writing task (see Table 2). We found partial support for the variability hypothesis in the letter naming task; participants in the hand-copying condition were more accurate than those in the tracing condition. We now discuss the theoretical and educational implications of these findings as well as their limitations and directions for future research.

Handwriting and alphabetic learning

Previous research has explored the benefits of handwriting experience in prereaders, with a primary focus on letter learning (e.g., Longcamp et al., 2005, 2008; Zemlock et al., 2018). Our findings align with these studies by underlining the critical role of graphomotor actions in developing alphabetic skills essential for successful reading and spelling. Children who received letter training through handwriting methods outperformed those trained with typing methods in various alphabetic learning tasks, including letter naming and letter writing. Importantly, whereas previous studies in this area predominantly used letter identification tasks to compare performance across training conditions, the current research extended this approach by also examining children's ability to name and write the trained letters.

Specifically, the letter identification task, which measures purely visual recognition of trained letter shapes, resulted in very high and similar recognition accuracy across all groups (~92%), demonstrating that children could correctly identify the trained letters among three distractors regardless of the training method. However, as stated in the Introduction, visual identification of letters is necessary but not sufficient for reading. The foundation of alphabetic learning as a critical skill for reading lies in the child's ability to understand the relationship between specific letter shapes and their corresponding sounds (Treiman, 2006), emphasizing that learning specific mappings between letters and sounds is the fundamental ability underlying reading (Caravolas et al., 2019; Torppa et al., 2016, 2020).

In this regard, previous studies on letter learning in children often did not include sounds during the training phase (Longcamp et al., 2005; Zemlock et al., 2018). Among the studies that did include sounds (e.g., Li & James, 2016), very few incorporated posttest measures to assess letter–sound mapping skills, such as translating letter shapes into sounds by naming them and retrieving the sound when seeing the letter by writing it to dictation (see Kiefer et al., 2015; Mayer et al., 2020). These tasks are crucial for understanding children's alphabetic learning. Importantly, our training design not only included listening to the sound while writing the letter to strengthen letter–sound mappings but also incorporated posttest tasks that offered detailed insights into children's alphabetic learning abilities.

Indeed, the letter naming task provides an excellent index of the child's ability to map a visual letter to its corresponding sound, which is predictive of further decoding ability. In our study, the advantage of naming the trained letters was substantial for handwriting, particularly for the hand-copying group, whose naming accuracy rate was 24% higher than that of the typing group. Notably, in the letter writing task, which entails greater memory demands due to the need to retrieve the letter shape while maintaining the sound in mind and making the movements (Treiman, 2006), the gap between the handwriting groups relative to the typing groups was even greater (~30%). These outcomes support the conclusion that graphomotor action led to better performance in alphabetic tasks than learning conditions lacking graphomotor activity. This benefit in both alphabetic learning measures was also observed by Wiley and Rapp (2021) in adults learning a novel script. Using a parallel letter–sound learning procedure, Wiley and Rapp reported an advantage of the handwriting group over the typing group in letter naming and letter writing tasks.

Overall, these findings indicate that graphomotor action is an effective mechanism for retaining letter representations and suggest that providing the phonological correlates of written letters during training enhances the learning of letter–sound mapping skills, which are critical for future reading and spelling (Aravena et al., 2018; Law et al., 2018). Moreover, previous studies suggest that the speed at which alphabetic knowledge is acquired during the learning phase facilitates the transition to orthographic learning (Sunde et al., 2020). In this context, graphomotor action appears to be an essential tool for optimizing the reading learning process from the very beginning.

Handwriting and orthographic learning

Regarding orthographic learning, our results also support the graphomotor hypothesis. As with alphabetic learning tasks, the two handwriting groups yielded substantially higher accuracy levels across the three posttest tasks assessing orthographic learning. The smallest gap between handwriting and typing groups was observed in the word identification task (12%). When children needed to decode the learned words, the difference in decoding accuracy between those who learned through graphomotor action and those who learned through typing was larger (32%). This gap increased further (60%) when the task involved writing the letter strings to dictation, extending the word writing outcomes reported by Wiley and Rapp (2021) with adults to a sample of prereaders. This pattern of results suggests that learning letter strings through hand-copying or tracing creates strong memory traces for visual identification and provides a better foundation for applying letter–sound mapping rules and translating sounds into written orthographic forms.

Thus, the current findings support the contribution of the graphomotor component to the retention of orthographic representations. This pattern aligns with the results of Kiefer et al. (2015), who trained 5-year-old children on actual letters of the German alphabet for 4 weeks using either handwriting (specifically hand-copying) or typing. They observed that children in the handwriting group outperformed those in the typing group in word reading and writing posttest tasks. As noted in the Introduction, Mayer et al. (2020) did not find handwriting benefits in tasks assessing word learning after training 5-year-old children on 16 actual letters of the German alphabet for 7 weeks using either hand-copying, writing with a stylus on a tablet, or typing. However, as acknowledged by Mayer et al., this was likely due to the low reliability of the data (only four words were included in the posttest, with low effect sizes) and the floor effects observed in the tasks (an average of 36% accuracy in word reading and 52% of correctly written letters in the word writing task).

The enhanced performance in word reading and writing tasks observed in children trained through graphomotor actions, both in Kiefer et al. (2015) and in our study, suggests that the ability to translate written letters into sounds while performing the corresponding movements strengthens the formation of stable word representations (Bosse et al., 2014). This rationale aligns with the findings of Shahar-Yames and Share (2008), who trained primary school children on novel words through viewing, writing, or decoding. Their posttest results showed that reading, writing, and orthographic choice performances were superior in the writing and decoding groups, with the greatest learning benefit observed in the writing group. Shahar-Yames and Share (2008) proposed that both decoding and writing compel children to focus on word-specific letter-to-sound mappings through phonological recoding, facilitating the construction of well-specified word representations. Although our study does not provide a framework to test these causal mechanisms (e.g., we did not manipulate the consistency of letter-to-sound mappings), it is plausible to speculate on the relationship between phonological recoding during handwriting and the learning of orthographic word forms. As children write or trace words, they can follow the sound–letter sequence more slowly, potentially enhancing the encoding of the letter string.

In contrast, typing on a keyboard might not provide a comparable opportunity to connect the sound–letter sequence with a sequence of contingent movements. From a perception–action perspective, handwriting integrates eye and hand movements, allowing the visual form and motor action to be fully coordinated (Fears & Lockman, 2019). Typing, however, requires splitting attention between the screen and the keyboard, which not only hinders the integration of visual and motor information but also increases cognitive load, making it more challenging to process phonological information in the graphemic buffer (Wollscheid et al., 2016). Eye movement studies indicate that as children develop, the automatization of motor actions facilitates the integration of complex visual stimuli such as letter strings. The reported relationship between the automatization of fine motor skills for handwriting and children's literacy achievement further supports this perspective (Cameron et al., 2016; Julius et al., 2016).

Importantly, our data showed that children in the hand-copying group outperformed those in the tracing group in letter naming, letter writing, word naming, and word writing tasks, with consistent numerical advantages across all measures, showing accuracy gaps of 18%, 19%, and 35%, respectively. The absence of differences between hand-copying and tracing on most tasks does not entirely rule out the possibility that variability plays a role in learning. Two factors should be considered in this regard: font diversity and amount of training time. Regarding font diversity, our study did not include a tracing condition with different fonts, as Li and James (2016) did, because the goal was to manipulate motor action and variability orthogonally under minimal conditions. Comparing tracing with varying fonts and hand-copying could provide further insights into the role of variability in children's learning. In addition, the variability generated by handwriting in their study was greater than that achieved with the two fonts used in our typing condition (note that Li & James, 2016, employed four different font types). Although children are often exposed to very few sans-serif fonts when using computers or digital devices (Wilkins et al., 2009), real-world digital contexts—such as school computers, mobile devices, and tablets—may expose them to more diverse letter variations than those included in our study. Regarding training duration, the smaller effects found for variability output may stem from the brief letter and word training period in our experimental setup. The limited exposure to different instances in our study is not comparable to the extensive experience children typically have when learning letters and words, potentially restricting their access to multiple variable instances of each category. As a result, our setup may have been less favorable for the tracing and typing conditions, as children primarily produce more diverse variations of letters and words through hand-copying, particularly when fine motor skills are still developing. Suggestions to address this limitation are discussed in the next section in the context of future studies.

Mechanisms underlying graphomotor action benefits: Handwriting versus typing

Why does graphomotor action favor the acquisition of letter and word representations over typing? One explanation is that the mental representations of letters and words integrate visuospatial and sensorimotor experiences linked to linguistic information (Mangen et al., 2015). The visual and kinetic components of motor execution are simultaneous, continuous, and spatiotemporally linked, which supports learning (Van der Weel & Van der Meer, 2024). In contrast, typing separates these processes, lacking motor information about stroke formation and failing to integrate visual and kinetic components, which may explain the limited learning effects observed in the typing groups (Mangen & Balsvik, 2016). Another explanation is that handwriting engages attentional resources less involved during typing (Seyll & Content, 2022). Attention to hand movements and the generated shapes may enhance the memorization and retrieval of letter and word properties. Notably, in the current study, the largest differences between handwriting and typing groups were found in tasks requiring the most memory effort, such as letter and word writing. Although further research is needed, the potential combination of perceptual and sensorimotor experiences with attentional engagement stresses the importance of handwriting in supporting children's alphabetic and orthographic learning in school settings.

Before drawing our conclusions, it is important to acknowledge and discuss certain limitations of our study. First, the sample size was relatively small, particularly because the children were assigned to one of the four experimental conditions in the 2×2 design. Although statistical power was sufficient for testing the two main effects, it may have been limited for detecting subtle interactions. Recruiting a large sample for an intervention study requiring multiple training sessions with preliterate children was challenging, so for practical reasons the sample size was designed to fit power estimates for detecting main effects. Our strategy was to recruit children from the same school and year, ensuring a similar background; indeed, all critical variables that could generate differences between groups were well-matched. Although most of our findings were statistically robust, a larger sample size would likely provide more definitive conclusions for subtle effects (e.g., when comparing word tasks in the hand-copying and tracing groups). Second, our findings revealed no differences between the two typing conditions, both of which exhibited remarkably similar low levels of accuracy in tasks related to orthographic knowledge. As previously stated, this low performance might result from the children's limited familiarity with keyboard use (see Ouellette & Tims, 2014), but it also raises the possibility that employing a wider range of fonts might offer a stronger test for the variability hypothesis. Further studies should explore whether font variability influences letter learning when typing longer and—as suggested with tracing—with a more extensive range of fonts. Finally, additional research should examine the long-term contributions of different writing methods to the retention of trained letters and words. Although immediate evaluation captures the effects of training on the short-term consolidation of representations (Kiefer et al., 2015; Li & James, 2016; Longcamp et al., 2005), both graphomotor processes and variability output may potentially play a key role in long-term retention by fostering stronger motor and sensory connections compared with other forms of learning (Longcamp et al., 2008; Mayer et al., 2020).

Conclusions

The current experiment has revealed the critical role of graphomotor action in acquiring reading skills in young children, demonstrating its contribution to alphabetic and orthographic learning. From a graphomotor action perspective, handwriting involves unique haptic, kinetic, and sensory experiences that, when combined with the integration of sensorimotor information during movement, support the formation of accurate and comprehensive multimodal representations of letters and words.

Far from being merely a communication tool, handwriting is a critical component in developing the foundations of written language.

A key educational implication of the current study is the significant impact of handwriting-focused instruction on the alphabetic and orthographic knowledge children acquire. Previous studies have demonstrated the direct benefits of handwriting on fine motor skills and manual dexterity (see Kiefer & Spitzer, 2023) as well as its indirect influence on children's general cognitive abilities beyond literacy acquisition, such as numerical skills (Fischer et al., 2018) and lexical processing (Winter et al., 2021). Our findings emphasize the pivotal role of handwriting in early childhood education. Given the potential for early learning disadvantages to affect a child's reading trajectory (Stanovich, 2009), we conclude that keyboards should complement, rather than replace, handwriting in literacy activities, especially before reading skills are firmly established.

CRediT authorship contribution statement

Gorka Ibaibarriaga: Writing – original draft, Investigation, Data curation. **Joana Acha:** Writing – review & editing, Project administration, Methodology, Conceptualization. **Manuel Perea:** Supervision, Project administration, Methodology, Formal analysis, Conceptualization.

Data availability

Data and materials are available in OSF file, explicitly presented in the paper

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