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The impact of graphic motor programs and detailed visual analysis on letter-like shape recognition

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ABSTRACT

Recent research suggests that graphic motor programs acquired through writing are part of letter representations and contribute to their recognition. Indeed, learning new letter-like shapes through handwriting gave rise to better recognition than learning through typing on a keyboard. However, handwriting and typing do not differ solely by the nature of the motor activity. Handwriting requires a detailed visual analysis in order to reproduce all elements of the target shape. In contrast, typing relies on visual discrimination between graphic forms and does not require such detailed processing. The aim of the present study was to disentangle the respective contribution of visual analysis and graphomotor knowledge. We compared handwriting and typing to learning by composition, a new method which requires a detailed visual analysis of the target without the specific graphomotor activity. Participants composed the target symbols by selecting elementary features from the set displayed on the screen and dragging them in the appropriate position. In four experiments, adult participants learned sets of symbols through handwriting, typing or composition. Recognition tests were administered immediately after the learning phase and again two to three weeks later. Taken together, the results of the four experiments confirm the importance of the detailed visual analysis and provide no evidence for an influence of motor knowledge.

1. Introduction

Reading is pervasive in our lives and constitutes a major pillar in education, but it is a relatively recent cultural invention which does not rely on a specific innate endowment and requires explicit instruction to be acquired. Learning to identify the individual letters of the writing system constitutes a critical stage in reading acquisition. Indeed, letter recognition ability is an important predictor of subsequent reading skills (Foulin, 2005; Lonigan et al., 2000; Näslund & Schneider, 1996; O'Connor & Jenkins, 1999; Scanlon & Vellutino, 1996). Moreover, most current models of word recognition assume that letter recognition is an essential and integral stage preceding word reading (Coltheart et al., 2001; Dehaene et al., 2005; McClelland & Rumelhart, 1981; Perry et al., 2007). Yet, relatively few studies concern the initial step of letter recognition as well as its development.

Letter recognition has generally been considered as a strictly visual process based on elementary features extraction (Coltheart et al., 2001; Grainger et al., 2008; McClelland & Rumelhart, 1981; Perry et al., 2007). However, in the recent years, several studies suggested the involvement of the motor system in this process (see for reviews James, 2017; Longcamp et al., 2010; Longcamp et al., 2016). In accordance with the visual conception, the majority of the studies investigating the brain areas involved in single letter processing identified activation in the left fusiform gyrus of the extrastriate visual cortex (Flowers et al., 2004; Garrett et al., 2000; James et al., 2005). Some studies even suggested that this area exhibits specialization for letters as it responds more during letter perception than for other types of objects perception such as faces (Wong et al., 2009) or non-letter graphic shapes like digits (James et al., 2005; Polk et al., 2002) and unfamiliar symbols (Flowers et al., 2004; James et al., 2005; Wong et al., 2009; but see Joseph et al., 2006; Joseph et al., 2003; Longcamp et al., 2003). According to Flowers (2004; see also James et al., 2005), this single-letter area would be located slightly anterior to the Visual Word Form Area (VWFA, Cohen et al., 2000; McCandliss et al., 2003), the area assumed to be functionally specialized in visual word recognition.

According to Dehaene and Cohen (2007), the functional specialization of the left fusiform gyrus for letter and word recognition is an example of « neuronal recycling ». In this view, a novel cultural object invades existing neural structures, « recycles » their initial (innate) functionality and reuses an ancient biological mechanism for a different

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role while inheriting many of its structural constraints. Neuroimaging studies support this assumption by demonstrating that reading acquisition produces changes in brain anatomy and function (Carreiras et al., 2009; Dehaene, Pegado, et al., 2010). Thus, before reading acquisition, an area of the left fusiform gyrus is devoted to object and face recognition (Dehaene et al., 2005; McCandliss et al., 2003). At the onset of reading acquisition, it starts to respond to orthographic stimuli in the learned script (Baker et al., 2007; Bolger et al., 2005; Brem et al., 2010) and progressively becomes functionally specialized for orthographic processing (Cohen & Dehaene, 2004; but see Price, 2012; Price & Devlin, 2003).

One difference between object and letter recognition concerns mirror discrimination. Humans as well as animals naturally treat mirror images as similar (Biederman & Cooper, 1991; Bornstein et al., 1978; Logothetis et al., 1995; Logothetis & Pauls, 1995; Rollenhagen & Olson, 2000). This phenomenon constitutes an advantage for visual recognition in terms of learning and survival because in natural settings mirror images are almost always different views of the same object. On the contrary, mirror generalization is deleterious for letter recognition. Actually, letter orientation is fixed and mirror discrimination is important for efficient reading and writing. In the best case, mirror inversion gives rise to a non-meaningful visual form. In the worst case, it gives rise to another letter (e.g., mirror pairs “b” and “d”, or “p” and “q”). Thus, when learning to read, the visual system has to overcome mirror generalization (Dehaene et al., 2005; Dehaene, Nakamura, et al., 2010; Pegado et al., 2011). Supporting this hypothesis, mirror confusions are among the most frequent errors made when learning to read and write (Cornell, 1985; see Schott, 2007 for a review) and are more numerous in individuals with reading disabilities (Lachmann & van Leeuwen, 2007; Terepocki et al., 2002; Wolff & Melngailis, 1996). In literate adults, the left fusiform gyrus continues to show mirror invariance for pictures of objects and animals but demonstrates mirror discrimination for words (Dehaene, Nakamura, et al., 2010) and letters (Pegado et al., 2011). Based on those data, Pegado et al. (2011) suggested that the left fusiform gyrus plays a crucial role in the discrimination of letter orientation.

However, some recent studies suggest that the motor programs acquired through handwriting may be an integral part of letter representations and facilitate letter recognition as well as the discrimination of letter orientation (James, 2010; Longcamp et al., 2006; Longcamp et al., 2008; Longcamp, Zerbato-Poudou, & Velay, 2005). Motor programs for letter-forms (allographs) are gradually constructed in memory through handwriting (van Galen, 1991; see Palmis et al., 2017, for a review). Longcamp et al. (2010) thus proposed that handwriting would lead to a multimodal representation of letters coupling visual and motor codes, with the latter critically helping to discriminate between a letter and its mirror image thanks to an automatic internal motor simulation during visual processing. This hypothesis connects letter perception to embodied cognition perspectives and assumes that action-perception links during learning play a crucial role in the construction of concepts, leading to multimodal representations of objects (Barsalou, 2008; Sullivan, 2018; Wilson, 2002). According to this view, perceiving an object in one single sensory modality is sufficient to activate the whole distributed multimodal representation which was engaged in previous encounters with the same object (Barsalou et al., 2003).

The hypothesis of an internal motor simulation during visual perception of letters is in line with the intervention of the mirror-neuron system (MNS) in action observation. The MNS supposes the existence of shared brain mechanisms underlying both execution of actions and observation of similar actions performed by other individuals (Gallese et al., 1996; see Rizzolatti & Craighero, 2004, for a review). The activation of mirror neurons in motor areas has been found while passively looking at both dynamic displays (Buccino et al., 2001; Fadiga et al., 1995; Hari et al., 1998) as well as static stimuli such as still photographs of action (Johnson-Frey et al., 2003; Nishitani & Hari, 2002). Furthermore, in monkeys, other neurons of the premotor cortex (the « canonical neurons ») respond during the visual perception of graspable objects even in the absence of any action depiction (Murata et al., 1997). Those neurons would respond to the sensori-motor attributes associated with a given manipulable object. In humans, motor area activation, more precisely in the left posterior parietal and the left ventral premotor cortex (the latter supposed to be the human homologue of the monkey's « canonical neurons » area), has also been found while passively seeing pictures of manipulable objects (Chao & Martin, 2000; Grèzes & Decety, 2002). This premotor activation is deemed to reflect the automatic internal simulation of the motor programs corresponding to the hand movements associated with the use of the perceived object (Chao & Martin, 2000; Mecklinger et al., 2002; Tucker & Ellis, 2001). Those data suggest that manipulable object representations are based on a sensori-motor network involving both a visual and a motor component.

Although letters are not manipulable objects, learning to read usually involves joint reading and writing activities. Consequently, as for manipulable objects, each letter, as a visual form, is associated to a movement (necessary to its production), and conversely a movement is associated to each visual form. Moreover, handwritten letters constitute static visual stimuli corresponding to traces of one's own or someone else's actions. Actually, Freyd (1983) and Babcock and Freyd (1988) already suggested some years ago that perceivers spontaneously extract dynamic information relating to motor actions when seeing static handwritten traces. Freyd (1983) showed that participants better recognized distorted pseudoletters if the distortion was consistent with the handwritten action that had been observed during the learning of the pseudoletters. Conversely, the handwritten action produced by participants after learning static distorted pseudoletters was consistent with the production rules associated with the distortions presented during learning (Babcock & Freyd, 1988). An impact of letter writing knowledge on letter identification has also been found in several neuropsychological studies (e.g., Anderson et al., 1990). For example, Schubert et al. (2018) observed that enhancing the activation of the graphic motor plan of a letter by showing information about its production improved recognition (see also Seki et al., 1995). Indeed, the visual presentation of letters drawn according to the typical writing trajectory led to higher recognition than the presentation of either static letters or dynamically-drawn letters following an atypical writing trajectory. The authors assumed that the stored graphic motor plans of letters are directly linked to abstract letter representations and that there are bi-directional connections between both components. In this view, activation can flow from abstract letter representations to graphic motor plans and conversely, from graphic motor plans to abstract letter representations (see also Bartolomeo et al., 2002).

The involvement of motor representations during visual letter processing is also supported by neuroimaging studies. The first ones to suggest a role of the motor system in Roman letters representation found unilateral premotor activation (left for right-handed and right for left-handed subjects) in participants looking passively at printed letters, even though they were not asked to read (James & Gauthier, 2006; Longcamp et al., 2003; Longcamp, Anton, et al., 2005). This activation was absent when looking to pseudoletters and it appeared precisely in the area engaged when writing the letters (Longcamp et al., 2003). The authors therefore suggested that this premotor zone may correspond to Exner's area, which is supposed to store the specific motor programs required to write letters (Anderson et al., 1990; Palmis et al., 2017; see Roux et al., 2010 for a review). Consequently, they assumed that the graphic motor programs acquired through handwriting are evoked when passively looking at letters and that the representation of letters is based on a sensori-motor network.

An additional source of evidence suggesting a contribution of the motor system to letter perception comes from behavioral studies showing that depriving participants of the graphomotor activity while learning new characters affected their subsequent recognition and

orientation discrimination (James, 2010; Longcamp, Zerbato-Poudou, & Velay, 2005; Longcamp et al., 2006, 2008). In Longcamp et al. studies, the learning method used to deprive learners from the graphomotor act was typewriting. There are some crucial differences in the hand movements required by both learning methods. Handwriting requires the execution of a sequence of fine movements that completely define the shape of the letter and lead to a unique association between a specified motor program and the letter form (Longcamp et al., 2006; Longcamp, Zerbato-Poudou, & Velay, 2005; Palmis et al., 2017; van Galen, 1991). By contrast, typewriting consists of a simple key-press movement associating a letter to an arbitrary key, and the choice of the key is based on the discrimination between graphic forms. This key press movement does obviously not include any information about the shape or the orientation of the letter. Moreover, no such specific correspondence between a movement and a given letter can be built because the hand movement trajectory depends on the previous position of the fingers (Logan, 1999; Longcamp, Zerbato-Poudou, & Velay, 2005; Longcamp et al., 2006, 2008).

Longcamp et al. (2010) explained the advantage of handwriting by the contribution of the writing memory during letter recognition. This assumption was supported by a neuroimaging study comparing the neural pathway activated during the recognition of characters which had been learned through handwriting versus typing. Premotor and parietal activation –regions known to be involved in motor execution and action observation– was observed after handwriting but not after typing, and occurred even though no motor response was required (Longcamp et al., 2008; see also James & Atwood, 2009). When a visual letter is presented, the motor program corresponding to the action necessary to produce it is automatically simulated and it is precisely the match or the mismatch between the visual information and the internal motor simulation that would help to avoid the confusion between the letter and its mirror-image. Indeed, whereas from a visual point of view a letter and its mirror-image are very similar, from a motor point of view, their respective motor programs are distinct and non-ambiguous. In contrast, for typed characters the visual ambiguity cannot be erased by the motor programs because no letter-specific graphomotor act has been executed during learning and therefore no motor representation tightly linked to the visual form could have been created in memory.

However, the comparison between training through handwriting and through typing allows for alternative interpretations. Actually, handwriting and typing do not differ only by the presence or absence of graphomotor activity and memory-stored graphic motor programs. Handwriting requires to carefully look at each feature of the target as well as their respective location and orientation. This detailed visual analysis may thus favor the construction of a detailed visual representation of the letter. Conversely, typing does not require such detailed processing since finding a match between the target and a key, based on any discriminant feature, would be sufficient to select the appropriate key. Consequently, the advantage of the handwriting method could be due to the detailed visual representation induced by handwriting rather than to the activation of the graphic motor program.

In accordance with this interpretation, graphic motor programs, the mental representations governing execution, are often described as abstract (effector-independent) codes defining the number of strokes and their spatiotemporal relations (Palmis et al., 2017; see also McCloskey et al., 2018). Moreover, in his analysis of writing processes, van Galen (1991) highlighted some specific characteristics of handwriting that support this interpretation. He insisted on the importance of stroke units in the final execution stage of the writing process, and he emphasized the serial aspect of letter production as the concatenation of strokes. Stroke units would be particularly important when learning unfamiliar graphic patterns at both the planning and execution stages (Hulstijn & van Galen, 1988; Portier et al., 1990), and it is likely that the visual system is highly solicited while constructing such detailed graphic motor programs. Indeed, a recent study reported stronger activation of the visual regions during the early stage of learning new graphomotor sequences than later on. This visual activation occurred in conjunction with premotor activation and was assumed to reflect the visuomotor mapping process which transforms visuospatial signals into motor commands (Swett et al., 2010).

The aim of the present study was to investigate the role of the detailed visual analysis induced by handwriting. Following the same logic as in previously mentioned learning studies (Longcamp, Zerbato-Poudou, & Velay, 2005; Longcamp et al., 2006, 2008; James, 2010), we experimentally manipulated the motor activity of adult participants while learning new symbols (i.e., unfamiliar graphic line shapes). In order to investigate the role of the detailed visual analysis, we added a third learning method (*composition*) with which participants had to reproduce the target symbol feature-by-feature. Thus, composition requires a detailed visual analysis but suppresses the letter-specific graphomotor activity. Participants reproduced the symbols through handwriting, through typing or through composition. After learning, they performed two recognition tests: a recognition test based on mirror-normal discrimination (Longcamp et al., 2006; Longcamp et al., 2008) and a four-alternative forced-choice recognition test requiring both mirror-normal discrimination and detailed visual analysis (James, 2010; Longcamp, Zerbato-Poudou, & Velay, 2005).

Based on previous findings, we expected higher recognition scores after handwriting than after typing. Regarding composition, three patterns of results could emerge depending on the theoretical perspective. If the graphic motor programs stored in memory are the key factor explaining the facilitatory effect incurred by handwriting in subsequent letter recognition (*graphomotor hypothesis*), handwriting training should lead to superior recognition performance than training through composition or typing, both giving rise to equivalent lower recognition levels. In contrast, if the detailed visual analysis required by handwriting is the source of its advantage (*visual analysis hypothesis*), learning through handwriting and composition should lead to equivalent subsequent recognition accuracy higher than with typing. Finally, if both the graphic motor programs and the detailed visual analysis contribute to the construction of letter representations (*mixed hypothesis*), three levels of recognition performance should emerge: better recognition following handwriting than composition, and better recognition following composition than typing. The first experiment aimed at assessing the respective contribution of motor knowledge and detailed visual analysis. Experiments 2 and 3 were conducted in order to disentangle the impact of the learning method from other possible confounds.

2. Experiment 1

The aim of this experiment was to examine the efficiency of learning new symbols, i.e. letter-like shapes, by composition, a method requiring a detailed visual analysis but no symbol-specific graphomotor activity, in the memorization of symbols. To this purpose, recognition accuracy incurred by composition was compared to that incurred by handwriting and typewriting.

2.1. Method

2.1.1. Participants

Sixty-three participants took part in the experiment. All were undergraduate students in higher education institutions in Brussels. Data from six participants were discarded, three because they reported history of dyslexia or attentional disorder and three because of a technical problem. There were 19 remaining participants in the handwriting group (*mean age* = 20.6 years; *SD* = 4.94), 20 in the typing group (*mean age* = 20.0 years; *SD* = 2.21) and 18 in the composition group (*mean age* = 19.4 years; *SD* = 1.72). There were six males and three left-handed participants. All reported normal or corrected-to-normal visual acuity. The study was approved by the local ethics committee.

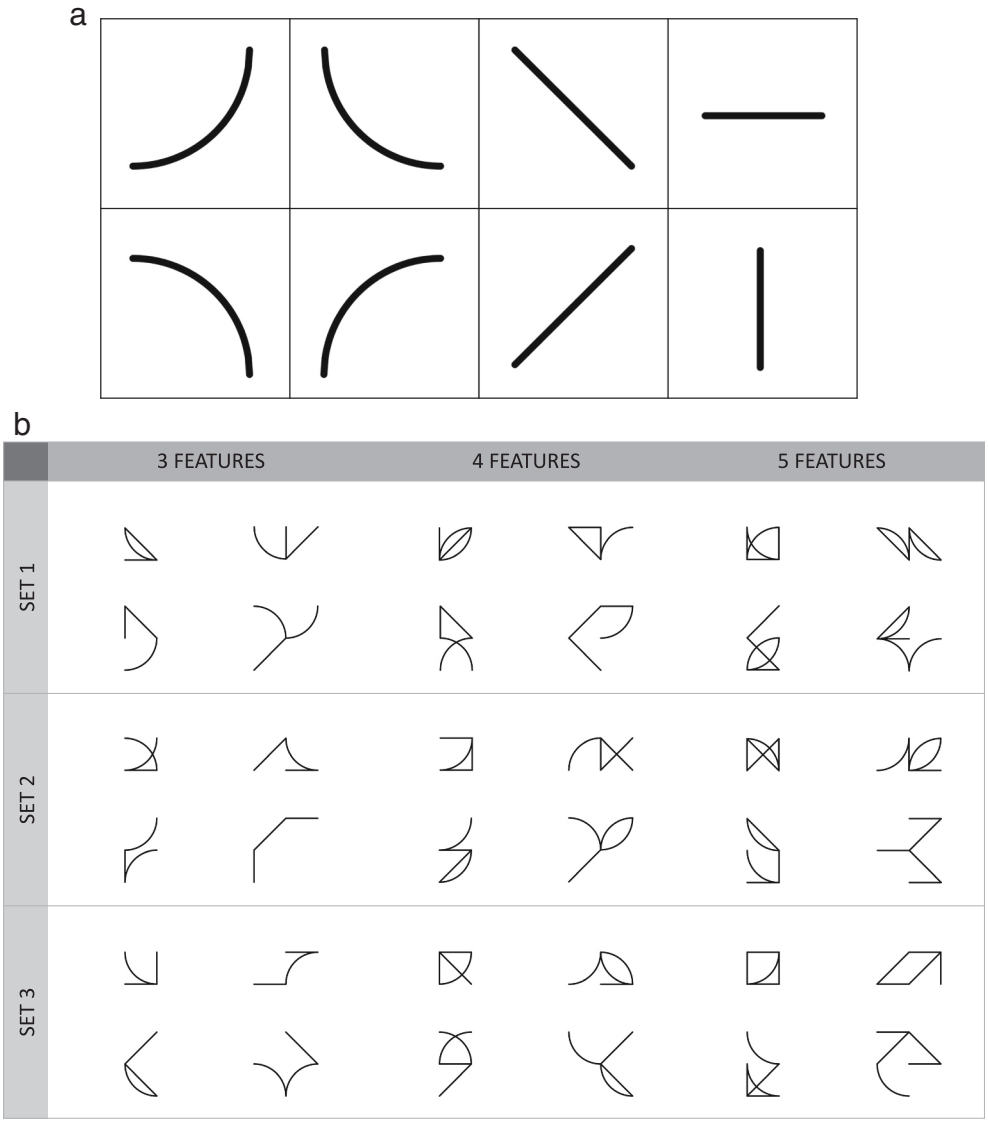

Fig. 1. (a) The eight elementary features used to construct the symbol library. (b) The three sets of 12 symbols to be learned.

2.1.2. Stimuli

Stimuli were symbols created from a set of eight elementary features (Fig. 1a). All possible symbols combining three, four or five features were generated, and we choose 12 symbols with three features, 12 with four features and 12 with five features. Those 36 symbols were divided into three sets of 12 (Fig. 1b), each set being assigned to one third of participants within each learning group.

2.1.3. Procedure

There were four sessions: the first two were dedicated to learning and the last two to the recognition tests. Participants came to the laboratory on two consecutive days for the learning sessions. The recognition tests were administered the day after the second learning session and again three weeks later. All participants learned 12 unfamiliar symbols. Participants were randomly assigned to one of three groups. One group learned the symbols by handwriting, the second group by typing and the third group by composition. All sessions took place in a quiet room and participants were tested individually. Participants were informed that they would be tested on recognition after the learning sessions.

For both the learning sessions and the recognition tests, presentation and response recording were programmed in Python using PsychoPy libraries. During learning, stimuli were displayed on a Wacom DTF-720 graphic tablet and participants responded with a stylus (used as a pen for handwriting and as a mouse for typing and composition). During recognition tests, stimuli were displayed on a 19" Samsung SyncMaster B1940W monitor (1280 × 1024-pixel resolution) and participants responded on the keyboard.

2.1.3.1. Learning phase. In each learning session, there were 12 blocks, each involving a random presentation of the 12 symbols. Participants could take a break between blocks if needed. Before training, they received three practice trials with simple geometric shapes (a circle, a square and a triangle). Feedback was given after each practice trials but not during learning.

The target symbol was horizontally centered on the tablet screen and was displayed in black in a white 37-mm-wide area against a grey background. It stayed visible on the screen during the whole trial and the transition to the next trial was triggered by the participant. No constraint was imposed on production speed.

2.1.3.1.1. Handwriting method. The screen was divided in two portions: the target symbol was displayed in the upper portion and the response area in the lower portion. Both had the same size and color (Fig. 2a). Participants had to copy the symbol in the response area.

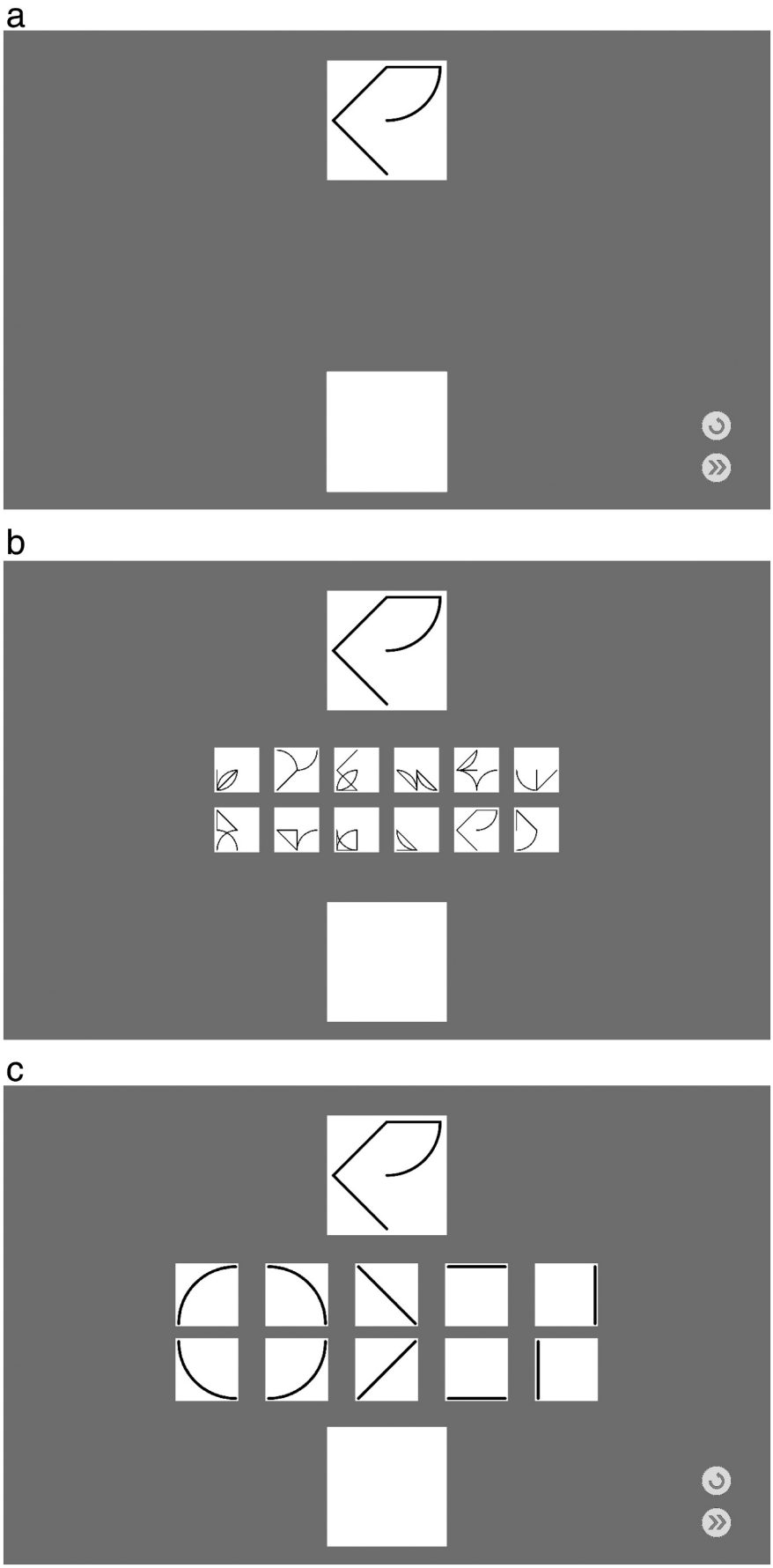

Fig. 2. One example of trial display for each learning method: (a) handwriting, (b) typing and (c) composition.

Those two portions were displayed during the entire trial. No constraint was imposed on stroke direction or order. To trigger the next trial, participants had to click on the "next" button displayed in the lower-right corner. If wished, they could restart their drawing by clicking on the "restart" button displayed above the "next" button. Productions and response times from target onset until the "next" button press were recorded.

2.1.3.1.2. Typing method. The screen was divided in three portions: the target symbol was displayed in the upper portion, the virtual keyboard in the middle portion and the response area in the lower portion (Fig. 2b). The virtual keyboard was composed of 12 14-mm-wide keys, corresponding to the 12 target symbols. The position of the keys varied randomly across trials in order to promote an active visual research. The response area was of the same size and color as the target area. Those three portions were displayed during the entire trial. Participants had to find the key corresponding to the target symbol and click on it. Responses triggered the apparition of the selected symbol in the response area for 1.5 s before the start of the next trial. Accuracy and response times from target onset until the key press were recorded. It should be noted that the "typing method" used in the present experiment is different from a typical typing task given that the position of the keys varied randomly across trials. In what follows, however, we will refer to it as « typing method » for the sake of clarity.

2.1.3.1.3. Composition method. The screen was divided in three portions: the target symbol was displayed in the upper portion, the set of individual features in the middle portion and the response area in the lower portion (Fig. 2c). The middle section was composed of ten features displayed in 20-mm-wide squares. The position of the features was kept constant across trials and across participants. The response area was of the same size and color as the target area. Those three portions were displayed during the entire trial. Participants had to compose the target symbol by selecting features in the feature area and dragging them in the appropriate position in the response area. No constraint was imposed on stroke order. To trigger the next trial, participants clicked on the "next" button displayed in the lower-right corner of the screen. If wished, they could restart their composition by clicking on the "restart" button displayed above the "next" button. Productions and response times from target onset until "next" button press were recorded.

2.1.3.2. Recognition tests. In both test sessions, participants performed first the four-alternative forced choice (4AFC) recognition test and second the old/new recognition test. Symbols were displayed in black in a white 60-mm-wide area against a black background.

2.1.3.2.1. 4AFC recognition test. Each trial consisted of the presentation of four symbols: the learned symbol plus three distractors, i.e., the mirror image of the symbol (mirror symbol), the learned symbol with a feature displaced (transformed symbol) and the mirror image of the transformed symbol (mirror transformed symbol) (see Fig. 3). The four symbols were randomly displayed next to each other in the middle portion of the screen and participants had to select the learned symbol by hitting the corresponding key on the keyboard (the E, R, U, and I keys, respectively). There were five blocks each involving the random presentation of the 12 symbols and their distractors. Participants could take a break between blocks. Before the test, they performed 10 practice trials, each displaying one digit and three Latin letters. Participants had to press the key corresponding to the digit. Feedback was given after each practice trial.

Each trial started with a centered fixation cross for 300 ms, followed by a 200 ms black screen. Then the four choices were displayed until the response. The intertrial interval was 500 ms. The main dependent measure was accuracy. Response speed was not emphasized, although response times from target onset were also recorded.

2.1.3.2.2. Old/new recognition test. The 24 experimental stimuli were the 12 learned symbols plus their mirror-image. Participants were asked to indicate as accurately and as quickly as possible (but accuracy was emphasized over speed) whether the target symbol was one they had learned or not. They responded by pressing either the N (yes) or the C (no) key of the keyboard with their index fingers. There were three blocks, each involving a random presentation of the 24 symbols. Participants could take a break between blocks. Before the test, they received 10 practice trials with uppercase Latin letters presented either in normal or in mirror-reversed form. Feedback was given after each practice trial. Trials started with a centered fixation cross for 300 ms, followed by a 200 ms black screen. Then the symbol was displayed centrally until the participant responded. The intertrial interval was 500 ms. Response times were measured from target onset.

2.2. Results

All data files are available at https://osf.io/x69nj/. Analyses are based on ANOVAs. To compare learning methods, contrasts will be used. Given the advantage of handwriting over typing observed in previous studies (Longcamp et al., 2006, 2008; Longcamp, Zerbato-Poudou, & Velay, 2005), handwriting will systematically be contrasted with typing. To assess the respective contribution of the graphic motor programs and detailed visual analysis, handwriting will be contrasted with composition.

2.2.1. Learning phase

Trial durations in the learning phase were submitted to an ANOVA with learning method (handwriting, composition, typing) as a between-subject factor and block as a within-subject factor. For the purpose of this analysis, we considered eight successive blocks, each consisting of three consecutive learning blocks. Mean trial durations for each method are plotted in Fig. 4. The main effect of learning method was significant, $F(2, 54) = 75.388$, $p < .0001$, $\eta_p^2 = 0.736$. Contrasts revealed significantly higher mean trial durations for handwriting ($M = 8923$ ms, $SD = 2293$) than for typing ($M = 3826$ ms, $SD = 400$), $t = 10.226$, $p < .0001$, but no significant difference between handwriting and composition ($M = 9323$ ms, $SD = 1394$), $t = 0.781$, $p = .438$. The main effect of block was also significant, $F(7, 378) = 90.531$, $p < .0001$, $\eta_p^2 = 0.626$. Finally, the learning method by block interaction was significant, $F(14, 378) = 14.970$, $p < .0001$, $\eta_p^2 = 0.357$, revealing a less pronounced learning slope for typing than for both handwriting and composition.

2.2.2. Recognition tests

Each recognition test was submitted to an ANOVA with learning method (handwriting, composition, typing) as a between-subject factor and time of test as a within-subject factor (immediate, delayed). Accuracy was analyzed in terms of proportion of correct responses for the 4AFC recognition test and in terms of *d'* scores for the old/new recognition test. As no emphasis was put on response times, they were not further analyzed. Response times on correct trials were around 2600 ms for the 4AFC test and around 1200 ms for the old/new test, and they were similar for all learning methods.

2.2.2.1. 4AFC recognition test. Mean percentages of correct responses are plotted in Fig. 5a. The main effect of learning method was significant, $F(2,54) = 4.258$, $p = .019$, $\eta_p^2 = 0.136$. Contrasts revealed a significantly higher proportion of correct responses after handwriting ($M = 87.1\%$, $SD = 8.95$) than after typing ($M = 78.5\%$, $SD = 14.3$), $t = 2.403$, $p = .020$, but no significant difference between proportion of correct responses following handwriting and composition ($M = 87.9\%$, $SD = 8.8$), $t = 0.234$, $p = .816$. The main effect of time of test was significant, $F(1,54) = 43.268$, $p < .0001$, $\eta_p^2 = 0.445$, reflecting a higher rate of correct responses immediately after learning ($M = 88.6\%$, $SD = 10.9$) than three weeks later ($M = 80.0\%$, $SD = 14.3$). The interaction was not significant, $F(2,54) = 0.662$, $p = .52$, $\eta_p^2 = 0.024$.

Error types are plotted in Fig. 5b. On average, participants selected

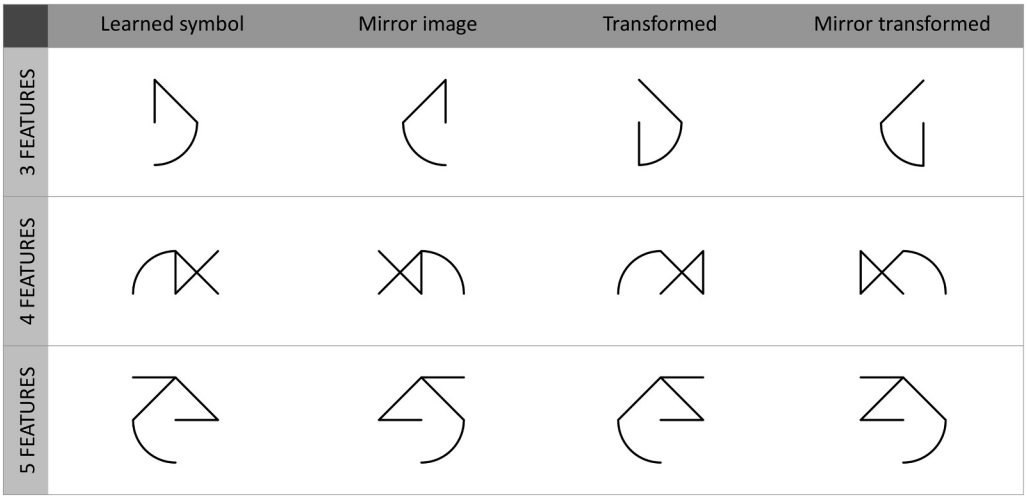

Fig. 3. Examples of trials in the 4AFC recognition test.

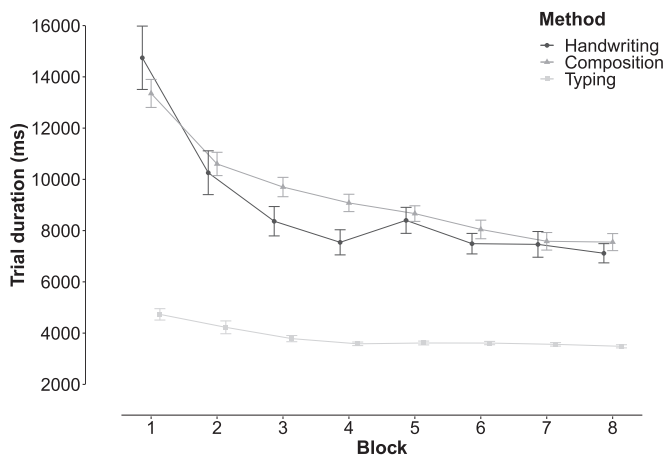

Fig. 4. Experiment 1: Mean learning trial duration across learning methods as a function of block. Error bars in all figures depict standard errors.

the mirror-image of the learned symbol on 12.2% of trials, the transformed symbol on 1.8% of trials, and the mirror transformed symbol on 1.6% of trials. An ANOVA performed on the rate of mirror-image choices revealed a significant difference between learning methods, $F(2, 54) = 4.242$, $p = .019$, $\eta_p^2 = 0.136$. A significantly higher proportion of mirror-symbol choices was observed after typing ($M = 16.9\%$, $SD = 11.1$) than after handwriting ($M = 10.5\%$, $SD = 8.1$), $t = 2.186$, $p = .033$, but there was no significant difference between handwriting and composition ($M = 8.8\%$, $SD = 7.5$), $t = 0.576$, $p = .567$.

2.2.2.2. Old/new recognition test. Here, accuracy was examined through the signal detection theory *d'* scores adapted to yes/no recognition tasks (Stanislaw & Todorov, 1999). The *d'* computation is based on separate calculations for responses to signal trials (hits and misses) from those to noise trials (correct rejections and false alarms). Typically, in a yes/no recognition task, old trials are considered as signal and new trials as noise (Stanislaw & Todorov, 1999). Mean *d'* scores are plotted in Fig. 6. In all conditions, *d'* scores were clearly above 0, indicating effective discrimination following all learning methods. The main effect of the learning method was significant, $F(2,54) = 4.383$, $p = .017$, $\eta_p^2 = 0.140$. Contrasts revealed that *d'* scores following handwriting ($M = 2.65$, $SD = 0.87$) were significantly higher than following typing ($M = 2.00$, $SD = 1.13$), $t = 2.086$, $p = .042$, but no significant

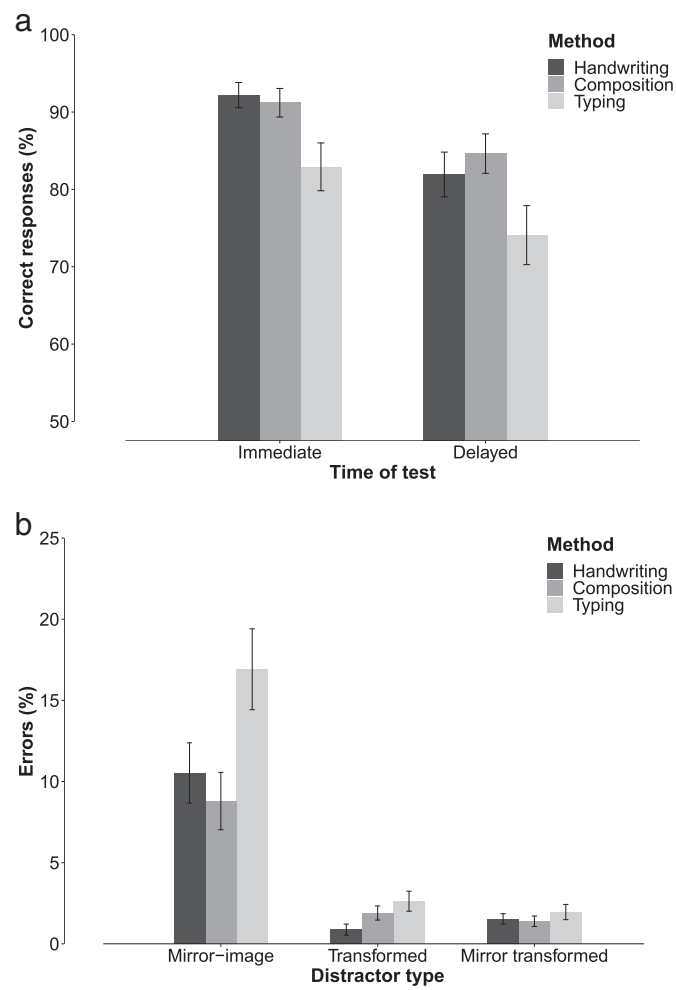

Fig. 5. Experiment 1: (a) Mean percentage of correct responses for the immediate and delayed 4AFC test across learning methods. (b) Errors produced across the three learning methods.

difference between *d'* scores following handwriting and composition ($M = 2.90$, $SD = 0.85$), $t = 0.778$, $p = .440$. The main effect of time of test was also significant, $F(1,54) = 84.777$, $p < .0001$, $\eta_p^2 = 0.611$, reflecting higher *d'* scores immediately after learning ($M = 2.93$, $SD = 1.13$) than three weeks later ($M = 2.07$, $SD = 1.03$). The

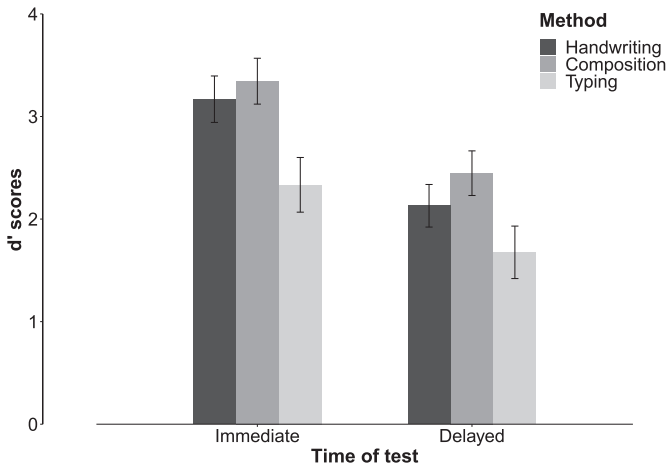

Fig. 6. Experiment 1: Mean *d'* scores for the immediate and delayed old/new test across learning methods.

interaction was not significant, $F(2,54) = 1.444$, $p = .245$, $\eta_p^2 = 0.051$.

2.3. Discussion

The aim of this experiment was to assess the efficiency of the composition method which involves a detailed visual analysis but suppresses the symbol-specific graphomotor component. When learning through this method, participants composed the symbols by selecting each feature of the target and positioning them at the correct location in the response area. The requirement of a detailed visual analysis, without relevant graphomotor activity allowed us to isolate the contribution of the former process in the construction of symbol representation in memory.

The analysis performed on trial duration during learning shows clear gains across blocks, thus indicating that some learning has occurred for the three methods, even though it appears to be more pronounced for handwriting and composition than for typing. For both recognition tests, participants were more accurate at recognizing the learned symbols after handwriting and composition than after typing.

The present data thus replicate the advantage of handwriting over typing observed in Longcamp et al.'s studies (2006, 2008). However, it should be noted that the patterns of results are not entirely comparable. In Longcamp et al.'s studies (2006, 2008), there was a learning method by time of test interaction that revealed an increasing advantage of handwriting over typing through time. Indeed, after handwriting, the recognition performance was stable over time whereas it decreased after typing. In contrast, the current data reveal a similar decrease of recognition accuracy over time after handwriting and after typing. The difference might be due to the lower amount of training in the present study than in Longcamp et al.'s studies (2006, 2008).

The comparable recognition performance observed after handwriting and composition suggests a contribution of the detailed visual analysis to the construction of symbol representation, and supports the visual analysis hypothesis according to which the advantage of handwriting over typing is caused by the sole implication of the detailed visual analysis. In other words, this experiment failed to reveal any advantage of the graphomotor programs acquired through handwriting on symbol recognition.

However, the experimental design allows for an alternative interpretation. Indeed, the three methods lead to large differences in total learning time, creating a possible confound which may question the prior interpretation. Actually, total learning time was much longer for both handwriting and composition than for typing. As shown in Fig. 4, each handwriting and composition trial lasted around nine seconds, more than twice the average duration of a typing trial. The lack of difference between handwriting and composition both in terms of learning duration and in terms of subsequent recognition, supports the importance of detailed visual analysis. However, it is arguable that the lower recognition following typing is due to total learning time rather than to the detailed visual analysis. The next experiment aimed at eliminating this learning time confound.

3. Experiment 2

The results of Experiment 1 suggest that the detailed visual analysis plays a key role in symbol memorization, given that learning by handwriting and composition led to higher recognition performance than learning by typing. However, the total learning time was quite different across the three learning methods, as composition and handwriting took significantly longer than typing. The lower performance observed following typing could thus also be explained by the shorter learning time. Experiment 2 aimed to disentangle the respective contribution of learning method and total learning time. To this purpose, we equated trial duration across the three methods. If the learning method is the source of subsequent recognition performance, a similar pattern of result to that of the previous experiment should be observed. In contrast, if total learning time is the key factor, similar recognition performance should emerge whatever the learning method.

3.1. Method

3.1.1. Participants

Sixty new participants took part in the experiment. All were undergraduate students in higher education institutions in Brussels. Data from three participants were discarded, two because they reported history of dyslexia and one because of a technical problem. There were 19 remaining participants in each of the three learning groups. The mean age of the 57 remaining participants was 20.7 years ($SD = 4.27$) (handwriting group: *mean age* = 20.5 years; $SD = 4.33$; typing group: *mean age* = 20.5 years; $SD = 3.27$; composition group: *mean age* = 21.2 years; $SD = 5.20$). There were 11 males and four left-handed participants. All reported normal or corrected-to-normal visual acuity. The study was approved by the local ethics committee.

3.1.2. Procedure and stimuli

Stimuli and procedure were the same as in Experiment 1, except for the three following elements. First, there were only two sessions, the first was dedicated to learning and was immediately followed by the recognition tests and the second took place two weeks later and was dedicated to the delayed tests. Second, there were only eight training blocks, each involving a random presentation of the 12 symbols. Third, trial duration during learning was fixed (11 s) whatever the learning method. All elements stayed visible on the screen until the end of the trial and participants were invited to remain focused on the symbol during the entire trial duration.

3.2. Results

3.2.1. Learning phase

Given the limitation of trial duration, participants could not always complete the copy or the composition. The percentage of completed productions was submitted to an ANOVA with learning method (handwriting, composition, typing) as a between-subject factor and block as a within-subject factor. For the purpose of this analysis, we considered four successive blocks, each consisting of two consecutive learning blocks. Percentages of completed productions are plotted in Fig. 7. The main effect of learning method was significant, $F(2, 54) = 15.53$, $p < .0001$, $\eta_p^2 = 0.365$. Contrasts revealed significantly higher proportions of completed productions in handwriting ($M = 97.9\%$, $SD = 2.37$) than in composition ($M = 87.8\%$,

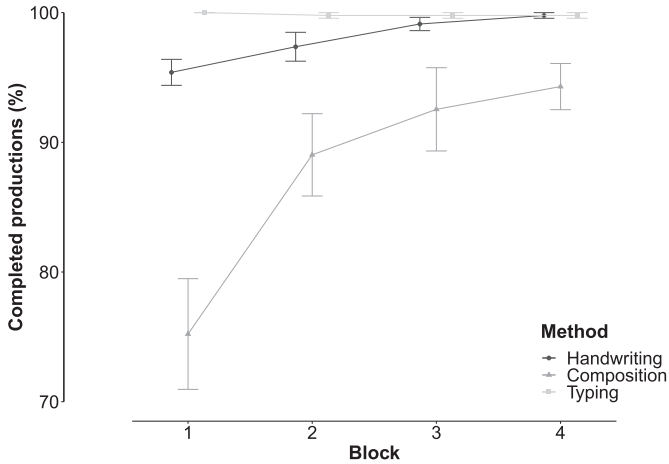

Fig. 7. Experiment 2: Mean proportion of completed learning trials across learning methods as a function of block.

SD = 12.2), t = 4.360, p < .0001, but no difference between handwriting and typing (M = 99.8%, SD = 0.39), t = 0.825, p = .413. The main effect of block was also significant, $F(3,162)$ = 27.26, p < .0001, η_p^2 = 0.335. Finally, the learning method by block interaction was significant, $F(6,162)$ = 15.87, p < .0001, η_p^2 = 0.370, revealing a more pronounced learning slope for composition than for handwriting and typing.

3.2.2. Recognition tests

Response times on correct trials were around 2700 ms for the 4AFC test and around 1200 ms for the old/new test, and similar for all learning methods.

3.2.2.1. 4AFC recognition test. Mean percentages of correct responses are plotted in Fig. 8a. The main effect of learning method was significant, $F(2,54)$ = 3.449, p = .039, η_p^2 = 0.113. Contrasts revealed a significantly higher proportion of correct responses after handwriting (M = 82.3%, SD = 12.6) than after typing (M = 70.0%, SD = 19.7), t = 2.615, p = .012, but no significant difference between handwriting and composition (M = 75.2%, SD = 9.14), t = 1.522, p = .134. The main effect of time of test was significant, $F(1,54)$ = 54.03, p < .0001, η_p^2 = 0.500, reflecting a higher rate of correct responses immediately after learning (M = 81.8%, SD = 16.1) than two weeks later (M = 69.9%, SD = 16.4). The interaction was not significant, $F(2,54)$ = 0.419, p = .660, η_p^2 = 0.015.

Error types are plotted in Fig. 8b. On average, participants selected the mirror-image of the learned symbol on 16.3% of trials, the transformed symbol on 4.5% of trials, and the mirror transformed symbol on 3.3% of trials. An ANOVA performed on the rate of mirror-image choices revealed that the main effect of learning method was marginally significant, $F(2, 54)$ = 2.732, p = .074, η_p^2 = 0.092. A significantly higher proportion of mirror-symbol choices was observed after typing (M = 19.2%, SD = 9.98) than after handwriting (M = 12.6%, SD = 9.1), t = 2.277, p = .027, and there was no significant difference between handwriting and composition (M = 17.2%, SD = 7.4), t = 1.594, p = .117.

3.2.2.2. Old/new recognition test. Mean d' scores are plotted in Fig. 9. The main effect of learning method was significant, $F(2,54)$ = 3.919, p = .026, η_p^2 = 0.127. Contrasts revealed that d' scores following handwriting (M = 2.43, SD = 0.93) were significantly higher than following typing (M = 1.61, SD = 1.12), t = 2.747, p = .008, and marginally significantly higher than following composition (M = 1.88, SD = 0.68), t = 1.843, p = .071. The main effect of time of test was significant, $F(1,54)$ = 50.839, p < .0001, η_p^2 = 0.485, reflecting higher d' scores immediately after learning (M = 2.31, SD = 1.07) than two weeks later (M = 1.64, SD = 1.00). The interaction was not significant, $F(2,54)$ = 0.439, p = .647, η_p^2 = 0.016.

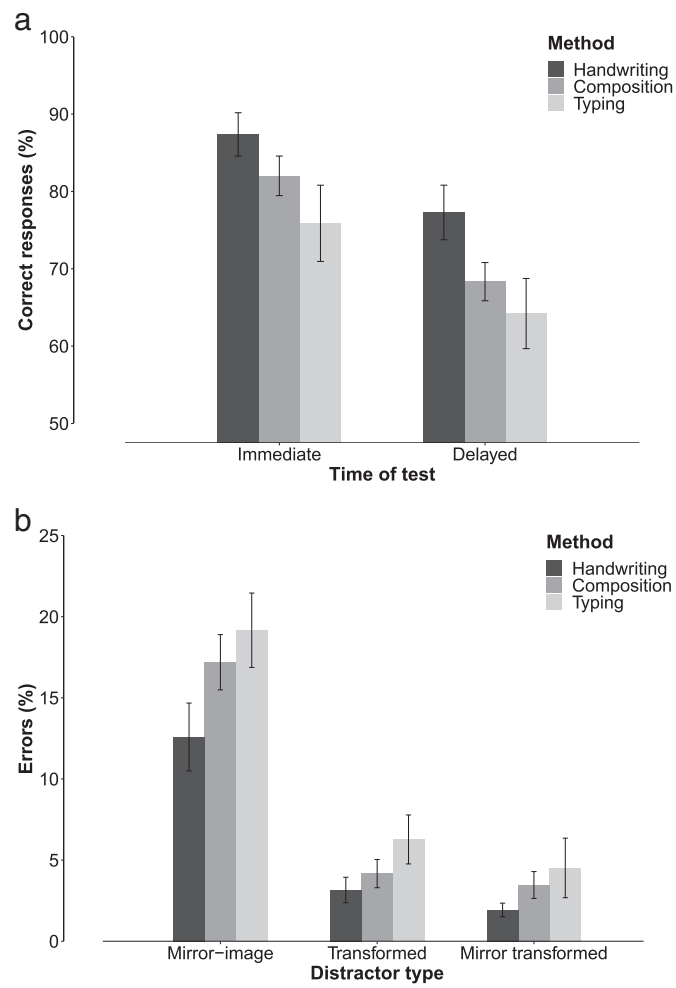

Fig. 8. Experiment 2: (a) Mean percentage of correct responses for the immediate and delayed 4AFC test across learning methods. (b) Errors produced across the three learning methods.

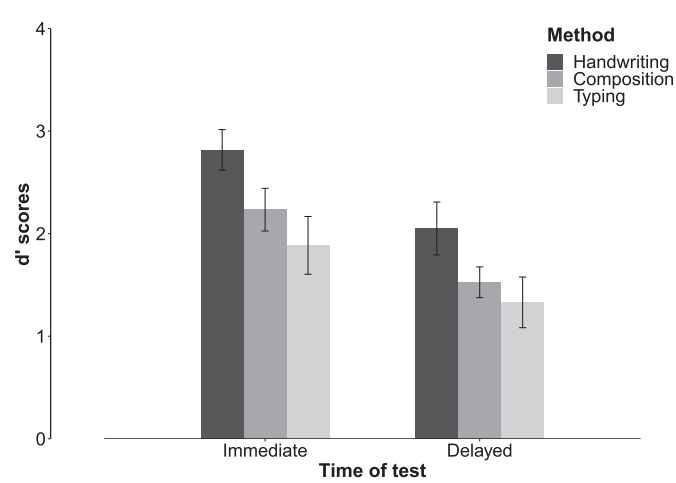

Fig. 9. Experiment 2: Mean d' scores for the immediate and delayed old/new test across learning methods.

3.3. Discussion

The aim of this experiment was to assess the role of learning time in symbol memorization. More precisely, we wondered whether the lower recognition accuracy observed after typing might be due to the shorter learning time incurred by this method. To ensure identical learning time for each learning method, we equated trial duration. As in Experiment 1, we found a clear advantage of handwriting over typing for both recognition tests. This suggests that total learning time is not the source of the advantage of handwriting and rather supports the importance of the learning method. However, composition led to an intermediate level of recognition falling between handwriting and typing, and the difference with handwriting was marginally significant in the old/new recognition test.

Limiting trial duration thus appears to have a detrimental impact on composition. The lower performance with the composition method may be due to the smaller amount of completed productions compared to typing or handwriting. Indeed, even if handwriting and composition take approximately the same amount of time when freely accomplished (see Experiment 1), composition led to more unfinished productions than handwriting under time constraints. Presumably, participants were able to adjust their writing velocity to the limited trial duration constraint, perhaps to the expense of some degree of copying precision. In contrast, it was harder to cope with the time constraint in the composition situation, and it is likely that this made composition a more stressful situation.

Furthermore, due to the large difference in normal completion time, trial duration was used very differently in the three learning situations. Typing was typically realized within 3–4 s and participants might not have stayed focused on the target during the entire trial. For handwriting, trial duration allowed participants to complete their production without leaving much free time. By contrast, for composition, the entire time slot was needed and was even sometimes insufficient to complete the production. Hence, despite the time per learning trial being equated across methods, participants were not equally active and probably not equally attentive to the symbols in the three learning situations. One might therefore wonder whether the advantage of handwriting over typing is due to the learning method or to the duration of *active* learning. Thus, equating trial duration across methods does not seem to offer the best option to control total learning time.

One way to control both learning time and active learning time would be to leave participants free to learn at their own pace within an equal total period of time. The next experiment aimed precisely at assessing the respective contribution of learning method and of active learning time in the memorization of symbols.

4. Experiment 3

Contrary to Experiment 1, in which no difference between handwriting and composition was obtained, the results of Experiment 2 are ambiguous, as the performance for composition fell between that of the two other methods and tended to be lower than for handwriting, though not significantly. As this pattern could be attributed to the time limitation, the aim of the present experiment was to assess the efficiency of the three learning methods while controlling for active learning time. One way to control both learning time and active learning time consists in assigning the same *total* learning time to each method, leaving participants free to trigger the transition to the next trial as soon as they finish the current one. If the learning method is the source of subsequent recognition performance differences, a similar pattern of results to that of Experiment 1 should be observed. In contrast, if active learning time is the key factor, similar recognition performance should emerge whatever the learning method.

However, this design may introduce another confound due to differences in the number of learning trials. Indeed, given that typing requires less time, participants would receive more learning trials with that method than with the others. For that reason, we also designed a condition in which learning was limited in terms of number of trials. Hence, two groups participated under different learning constraints. Each group learned three sets of symbols, one with each learning method and the manipulation of learning method was within-participants, as in Longcamp et al. (2006, 2008). In the fixed-time condition (Experiment 3a), learning time was equal for each method but the number of learning trials varied whereas in the fixed-number condition (Experiment 3b), the number of learning trials was equal for each method but learning time varied.

4.1. Method

In Experiment 3a, learning exposure was limited in terms of total learning time. Each learning session lasted exactly 12 min. The eight symbols were repeatedly presented in random order until the 12 min were elapsed. Hence, the number of learning trials varied across learning methods. In Experiment 3b, learning exposure was limited in terms of number of trials. Participants received 12 blocks of eight symbols for each learning method. Thus, the number of learning trials was fixed but the total learning time was free to vary across learning methods.

4.1.1. Participants

All were undergraduate students in higher education institutions in Brussels. Data from one participant were discarded because of a technical problem. Thirty new participants were assigned to each experiment. In Experiment 3a, mean age was 23.5 years (SD = 3.61). There were nine males and four left-handed participants. In Experiment 3b, mean age was 23.6 years (SD = 2.92). There were 10 males and one left-handed participants. All participants reported normal or corrected-to-normal visual acuity. The study was approved by the local ethics committee.

4.1.2. Procedure and stimuli

The procedure was similar to that of Experiment 2 with one major design change. Participants learned three sets of eight symbols, one set through each learning method. The association between sets of symbols and learning methods was counterbalanced across participants. Participants could take a break every 12 min in Experiment 3a and every three blocks in Experiment 3b. Whatever the learning method, the transition to the next trial was triggered by the participant. The three learning methods were administered sequentially during a single session in an order counterbalanced across participants. Each learning method was announced by an instruction screen.

In addition, because the total number of symbols to be learned was double, slightly simpler stimuli composed of three or four features were used. A tactile tablet was used (Wacom Cintiq 13HDT) so that participants responded by touch rather than with a stylus. The virtual keyboard of the typing method was composed of all 24 target symbols to be learned. For the handwriting method, paper and pen was used rather than the tablet. Participants were given 67.5 × 105 mm notebooks, and had to copy one symbol per sheet within a square of 17 × 17 mm. They were not allowed to flip back through the notebook.

Testing procedure was identical to previous experiments. There were 24 and 48 trials per block, respectively for the 4AFC and the old/new recognition tests.

4.2. Results

4.2.1. Experiment 3a

4.2.1.1. Learning phase. The number of presentations of each symbol in the learning phase was submitted to an ANOVA with learning method (handwriting, composition, typing) as a within-subject factor. The mean number of symbol presentations for each method is plotted in Fig. 10. The main effect of the learning method was significant, F

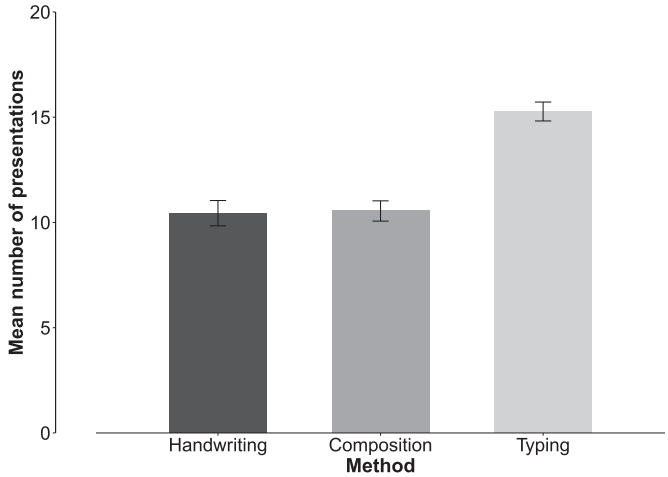

Fig. 10. Experiment 3a: mean number of presentations of each symbol across learning methods.

(2,58) = 37.74, $p < .0001$, $\eta_p^2 = 0.566$. Contrasts revealed a lower number of symbol presentations for handwriting ($M = 10.4$, $SD = 3.3$) than for typing ($M = 15.3$, $SD = 2.5$), $t = 7.605$, $p < .0001$, but no significant difference between handwriting and composition ($M = 10.5$, $SD = 2.6$), $t = 0.164$, $p = .870$.

4.2.1.2. Recognition tests. Each recognition test was submitted to an ANOVA with learning method (handwriting, composition, typing) and time of test (immediate, delayed) as within-subject factors. Response times on correct trials were around 3700 ms for the 4AFC test and around 1300 ms for the old/new test.

4.2.1.2.1. 4AFC recognition test. Mean percentages of correct responses are plotted in Fig. 11a. The main effect of learning method was not significant, $F(2,58) = 0.664$, $p = .519$, $\eta_p^2 = 0.022$. Contrasts revealed neither significant difference between handwriting ($M = 68.1\%$, $SD = 16.9$) and typing ($M = 64.9\%$, $SD = 13.9$), $t = 1.055$, $p = .296$, nor between handwriting and composition ($M = 65.3\%$, $SD = 18.0$), $t = 0.930$, $p = .356$. The main effect of time of test was significant, $F(1,29) = 84.68$, $p < .0001$, $\eta_p^2 = 0.745$, reflecting a higher rate of correct responses immediately after learning (M = 73.9%, $SD = 14.0$) than two weeks later (M = 58.2%, $SD = 14.3$). The interaction was not significant, $F(2,58) = 0.003$, $p = .997$, $\eta_p^2 = 0.000$.

Error types are plotted in Fig. 11b. On average, participants selected the mirror-image of the learned symbol on 21.3% of trials, the transformed symbol on 6.9% of trials, and the mirror transformed symbol on 5.7% of trials. An ANOVA performed on the rate of mirror-image choices revealed a significant difference between learning methods, $F(2, 58) = 3.782$, $p = .029$, $\eta_p^2 = 0.115$. Proportion of mirror-symbol choices after handwriting ($M = 17.6\%$, $SD = 11.1$) was significantly lower than after typing ($M = 24.0\%$, $SD = 10.5$), $t = 2.645$, $p = .011$, and marginally significantly lower than after composition ($M = 22.4\%$, $SD = 10.5$), $t = 1.975$, $p = .053$.

4.2.1.2.2. Old/new recognition test. Mean *d'* scores are plotted in Fig. 12. The main effect of learning method was not significant, $F(2,58) = 2.150$, $p = .126$, $\eta_p^2 = 0.069$. However, contrasts revealed higher *d'* scores after handwriting ($M = 1.42$, $SD = 1.01$) than after typing ($M = 1.06$, $SD = 0.84$), $t = 2.020$, $p = .048$, and no difference between handwriting and composition ($M = 1.16$, $SD = 0.94$), $t = 1.418$, $p = .162$. The main effect of time of test was significant, $F(1,29) = 37.18$, $p < .0001$, $\eta_p^2 = 0.562$, reflecting higher *d'* scores immediately after learning ($M = 1.51$, $SD = 0.90$) than two weeks later ($M = 0.91$, $SD = 0.65$). The interaction was not significant, $F(2,58) = 0.486$, $p = .617$, $\eta_p^2 = 0.016$.

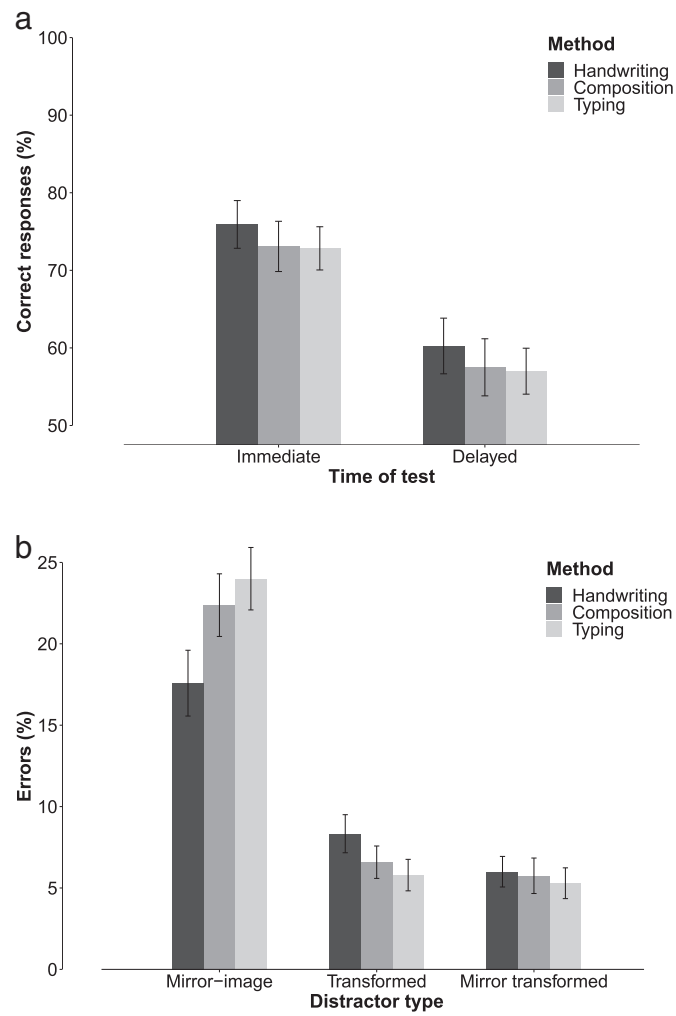

Fig. 11. Experiment 3a: (a) Mean percentage of correct responses for the immediate and delayed 4AFC test across learning methods. (b) Errors produced across the three learning methods.

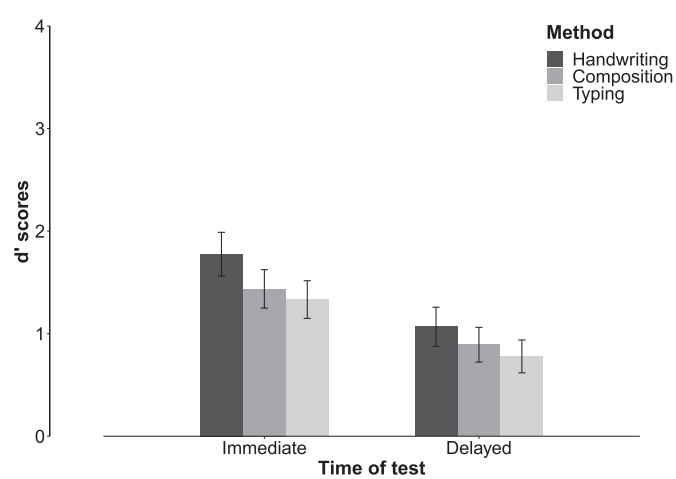

Fig. 12. Experiment 3a: mean *d'* scores for the immediate and delayed old/new test across learning methods.

4.2.2. Experiment 3b

4.2.2.1. Learning phase. Trial durations in the learning phase were submitted to an ANOVA with learning method (handwriting, composition, typing) and block as within-subject factors. For the

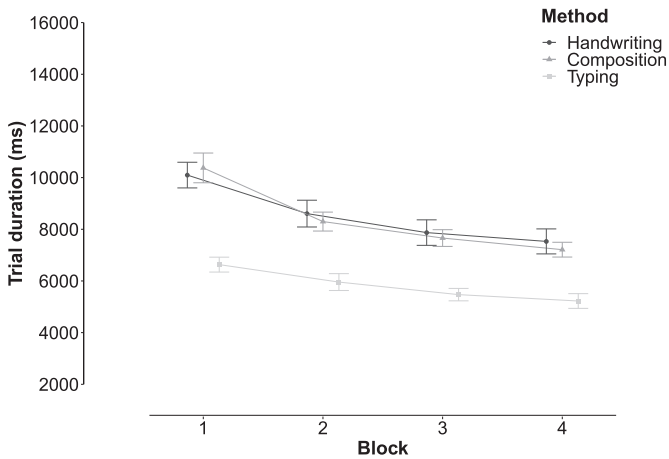

Fig. 13. Experiment 3b: Mean learning trial duration across learning methods as a function of block.

purpose of this analysis, we considered four successive blocks, each consisting of three consecutive learning blocks. Mean trial durations for each method are plotted in Fig. 13. The main effect of learning method was significant, $F(2, 58) = 35.199$, $p < .0001$, $\eta_p^2 = 0.548$. Contrasts revealed significantly higher mean trial durations for handwriting ($M = 8527$ ms, $SD = 2584$) than for typing ($M = 5821$ ms, $SD = 1435$), $t = 7.452$, $p < .0001$, but no significant difference between handwriting and composition ($M = 8387$ ms, $SD = 2040$), $t = 0.387$, $p = .700$. The main effect of block was also significant, $F(3, 87) = 107.397$, $p < .0001$, $\eta_p^2 = 0.787$. Finally, the learning method by block interaction was significant, $F(14, 174) = 6.139$, $p < .0001$, $\eta_p^2 = 0.175$, revealing a less pronounced learning slope for typing than for both handwriting and composition.

4.2.2.2. Recognition tests. Response times on correct trials were around 3600 ms for the 4AFC test and around 1300 ms for the old/new test.

4.2.2.2.1. 4AFC recognition test. Mean percentages of correct responses are plotted in Fig. 14a. The main effect of learning method was significant, $F(2,58) = 5.856$, $p = .0048$, $\eta_p^2 = 0.168$. Contrasts revealed a significantly higher proportion of correct responses after handwriting ($M = 73.8\%$, $SD = 13.6$) than after typing ($M = 66.9\%$, $SD = 16.7$), $t = 2.982$, $p = .004$, but no significant difference between handwriting and composition ($M = 73.8\%$, $SD = 13.8$), $t = 0.036$, $p = .971$. The main effect of time of test was significant, $F(1,29) = 79.91$, $p < .0001$, $\eta_p^2 = 0.734$, reflecting a higher rate of correct responses immediately after learning ($M = 78.9\%$, $SD = 11.5$) than two weeks later ($M = 64.1\%$, $SD = 15.4$). The interaction was not significant, $F(2,58) = 1.099$, $p = .340$, $\eta_p^2 = 0.037$.

Error types are plotted in Fig. 14b. On average, participants selected the mirror-image of the learned symbol on 17.8% of trials, the transformed symbol on 5.9% of trials, and the mirror transformed symbol on 4.8% of trials. An ANOVA performed on the rate of mirror-image choices revealed a significant difference between learning methods, $F(2, 58) = 4.381$, $p = .017$, $\eta_p^2 = 0.131$. A significantly higher proportion of mirror-symbol choices was observed after typing ($M = 21.1\%$, $SD = 12.4$) than after handwriting ($M = 16.5\%$, $SD = 10.7$), $t = 2.384$, $p = .020$, and there was no significant difference between handwriting and composition ($M = 15.9\%$, $SD = 9.7$), $t = 0.328$, $p = .744$.

4.2.2.2.2. Old/new recognition test. Mean *d'* scores are plotted in Fig. 15. The main effect of learning method was significant, $F(2,58) = 7.435$, $p = .0013$, $\eta_p^2 = 0.204$. Contrasts revealed higher *d'* scores after handwriting ($M = 1.71$, $SD = 0.95$) than after typing ($M = 1.19$, $SD = 1.06$), $t = 3.191$, $p = .0023$, but no difference between handwriting and composition ($M = 1.75$, $SD = 1.01$), $t = 0.280$, $p = .780$. The main effect of time of test was significant,

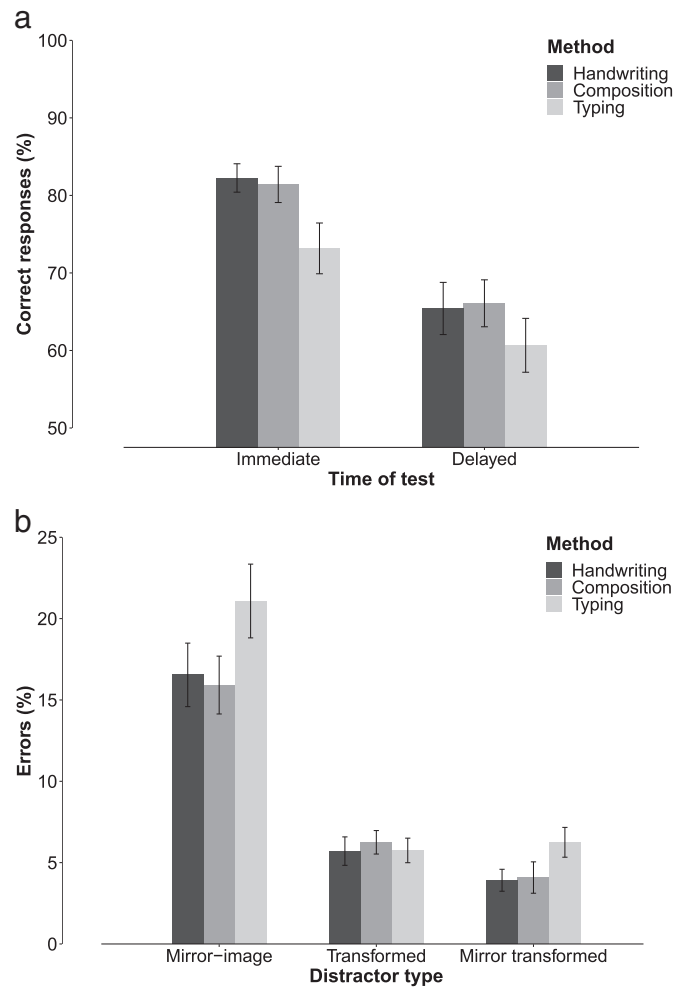

Fig. 14. Experiment 3b: (a) Mean percentage of correct responses for the immediate and delayed 4AFC test across learning methods. (b) Errors produced across the three learning methods.

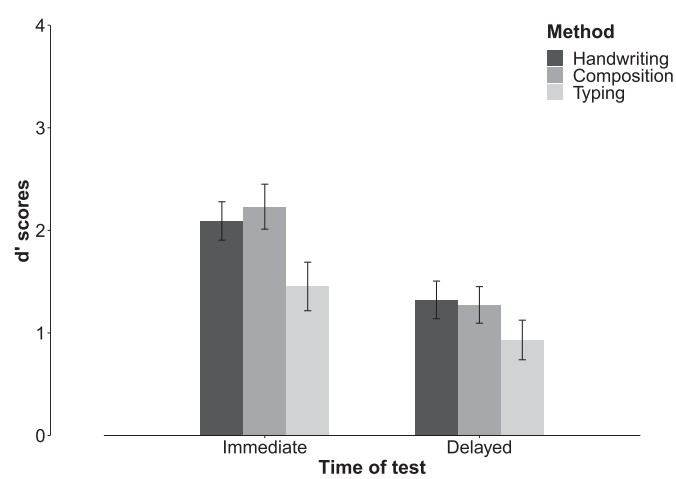

Fig. 15. Experiment 3b: mean *d'* scores for the immediate and delayed old/new test across learning methods.

$F(1,29) = 45.857$, $p < .0001$, $\eta_p^2 = 0.613$, reflecting a higher *d'* score immediately after learning ($M = 1.93$, $SD = 0.97$) than two weeks later ($M = 1.18$, $SD = 0.87$). The interaction was not significant, $F(2,58) = 2.199$, $p = .120$, $\eta_p^2 = 0.070$.

4.2.3. Comparison between experiments 3a and 3b

To compare experiments 3a and 3b, recognition performance was submitted to common analyses. For each recognition test, separate ANOVAs were performed on both contrasts, between handwriting and typing on the one hand, and between handwriting and composition on the other. Each set of data was submitted to ANOVAs with learning method (handwriting vs typing, or handwriting vs composition) and time of test as within-subject factors (immediate, delayed), and experiment (3a, 3b) as a between-subject factor.

4.2.3.1. Handwriting vs typing

4.2.3.1.1. 4AFC recognition test. The main effects of learning method and time of test were significant, respectively $F(1,58) = 6.027$, $p = .017$, $\eta_p^2 = 0.094$ and $F(1,58) = 106.190$, $p < .0001$, $\eta_p^2 = 0.647$. Neither the main effect of experiment, $F(1,58) = 1.306$, $p = .258$, $\eta_p^2 = 0.022$, nor the interaction of learning method by experiment, $F(1,58) = 0.834$, $p = .365$, $\eta_p^2 = 0.014$, or any other interaction reached significance.

4.2.3.1.2. Old/new recognition test. The main effects of learning method and time of test were significant, respectively $F(1,58) = 11.091$, $p = .002$, $\eta_p^2 = 0.161$ and $F(1,58) = 50.844$, $p < .0001$, $\eta_p^2 = 0.467$. Neither the main effect of experiment, $F(1,58) = 0.997$, $p = .322$, $\eta_p^2 = 0.017$, nor the learning method by experiment interaction, $F(1,58) = 0.318$, $p = .575$, $\eta_p^2 = 0.005$, or any other interaction reached significance.

4.2.3.2. Handwriting vs composition

4.2.3.2.1. 4AFC recognition test. The main effects of learning method was not significant, $F(1,58) = 0.595$, $p = .444$, $\eta_p^2 = 0.010$ but the main effect of time of test was significant, $F(1,58) = 158.455$, $p < .0001$, $\eta_p^2 = 0.732$. The main effect of experiment was marginally significant, $F(1,58) = 3.897$, $p = .053$, $\eta_p^2 = 0.063$. Recognition performance tended to be higher in Experiment 3b than in Experiment 3a. The learning method by experiment interaction was not significant, $F(1,58) = 0.528$, $p = .470$, $\eta_p^2 = 0.009$, nor any of the other interactions.

4.2.3.2.2. Old/new recognition test. The main effects of learning method was not significant, $F(1,58) = 0.760$, $p = .387$, $\eta_p^2 = 0.013$ but the main effect of time of test was significant, $F(1,58) = 92.920$, $p < .0001$, $\eta_p^2 = 0.616$. The main effect of experiment was marginally significant, $F(1,58) = 3.925$, $p = .052$, $\eta_p^2 = 0.063$. Recognition performance tended to be higher in Experiment 3b than in Experiment 3a. The learning method by experiment interaction was not significant, $F(1,58) = 1.548$, $p = .218$, $\eta_p^2 = 0.026$, nor any of the other interactions.

4.3. Discussion

The aim of this experiment was to assess the respective contribution of learning method and of active learning time in the memorization of symbols. To this purpose, participants learned the symbols at their own pace and learning exposure was either limited in terms of learning time, or in terms of number of trials. In the first case, participants had the same total learning time with the three methods but a variable number of trials (Experiment 3a). In the second case, with a fixed number of trials, they benefitted from a different total learning time with each method (Experiment 3b).

When exposure was limited in terms of total learning time, results still revealed higher recognition performance after handwriting than after typing even though the effect was less robust than in the other experiments. Indeed, on the one hand, contrasts performed on the *d'* scores of the old/new recognition test as well as analyses performed on the mirror-choice errors of the 4AFC test revealed better recognition levels after handwriting than after typing. On the other hand, ANOVAs failed to reveal any main effect of the learning method, either for the 4AFC recognition test, or for the old/new recognition test. Given that active learning time was equated, those findings thus suggest that the advantage of handwriting over typing is not solely due to active learning time. Regarding the comparison between handwriting and composition, no significant difference between both learning methods emerged, but there was a marginally significant trend towards more mirror-image errors following learning by composition.

When exposure was limited in terms of number of trials, the pattern of results was identical to that in Experiment 1. Handwriting led to higher recognition rates than typing, and no difference between handwriting and composition came out. Moreover, composition and handwriting were fully comparable in the learning phase given that they both led to similar trial time and thus to similar total learning time and active learning time. The absence of any clear difference in recognition performance between handwriting and composition does not favor the graphomotor hypothesis and rather supports the visual analysis hypothesis.

In order to assess the contribution of active learning time, experiments 3a and 3b were submitted to common analyses. None of these revealed a significant interaction between experiment and learning method, which suggests that active learning time does not play a crucial role. To sum up, in both experiments, handwriting led to better recognition than typing and no robust difference emerged between handwriting and composition, again supporting the visual analysis hypothesis over the graphomotor hypothesis.

5. General discussion

Recent studies suggest that the motor knowledge acquired through handwriting would help to identify letters and to discriminate them from other visually close graphic shapes. This assumption is based on the observation that learning new characters through handwriting leads to higher subsequent recognition than other learning methods which do not involve any letter-specific action (James, 2010; Longcamp et al., 2006, 2008; Longcamp, Zerbato-Poudou, & Velay, 2005). We argued that the advantage of handwriting over typing might be explained by the detailed visual analysis required by handwriting rather than by the activation of graphic motor programs. The goal of the present study was to explore the contribution of the detailed visual analysis in the handwriting advantage observed in previous studies. To this purpose, in addition to handwriting and typewriting, we introduced a new method, learning by composition, which requires a detailed visual analysis of the target but does not involve any specific graphomotor activity.

In Experiment 1, participants learned at their own pace for a fixed number of trials and the results showed that handwriting and composition took longer than typing. In order to equate total learning time, Experiment 2 fixed trial duration as well as number of trials. However, participants were not equally active in the three learning conditions due to the large difference in trial completion times. To control for active learning time, Experiment 3a allowed participants to learn at their own pace for a fixed total duration. Because this control induced differences in the number of learning trials, Experiment 3b used the same design and stimuli but limited exposure in terms of number of trials (as in Experiment 1).

Table 1 displays the main findings of the four experiments. Whatever the experiment, recognition performance following handwriting was better than after typing and the effect was clearly significant in experiments 1, 2 and 3b. Experiment 1 indicates that the advantage is not due to the number of learning trials. Experiment 2 confirms the previous conclusion and suggests moreover that it cannot be explained by total learning time. This latter experiment is in line with Longcamp et al. studies (2006, 2008) which found a similar advantage of handwriting over typing when trial duration was equated across methods. Experiment 3b replicates the results of Experiment 1 with a within-subject design. Finally, the persistence of the handwriting advantage in Experiment 3a suggests that the beneficial impact of handwriting is not due to total active learning time. Furthermore, the absence of

Table 1
Synopsis of the results. The experimental controls are shown in bold and the observed relations in italic.

	Recognition performance	Number of trials	Total learning time	Total active learning time
Handwriting > Typing ?				
Experiment 1	*HW > T*	**HW = T**	*HW > T*	*HW > T*
Experiment 2	*HW > T*	**HW = T**	**HW = T**	*HW > T*
Experiment 3a	*HW > T*[a]	*HW < T*	**HW = T**	**HW = T**
Experiment 3b	*HW > T*	**HW = T**	*HW > T*	*HW > T*
Handwriting > Composition ?				
Experiment 1	*No difference*	**HW = C**	*No difference*	*No difference*
Experiment 2	*No difference*[b]	**HW = C**	**HW = C**	*HW < C*
Experiment 3a	*No difference*[c]	*No difference*	**HW = C**	**HW = C**
Experiment 3b	*No difference*	**HW = C**	*No difference*	*No difference*

[a] No significant effect was observed in the ANOVAs, but the HW vs T contrast on the *d'* scores of the old/new recognition test as well as on the mirror-choice errors of the 4AFC test revealed better recognition levels after handwriting than after typing.

[b] The contrast on the old/new recognition test revealed a marginally significant difference.

[c] The contrast on the mirror-image choices of the 4AFC recognition test revealed a marginally significant difference.

interaction between Experiment and Learning method when comparing Experiment 3a and 3b reinforces the conclusion that neither the number of trials, nor the total learning time, nor the total active learning time constitutes the source of the advantage of handwriting over typing.

Regarding handwriting and composition, when participants learned at their own pace (experiments 1, 3a and 3b), both conditions were fully comparable regarding the learning phase (see Table 1). Indeed, both methods led to similar trial durations and thus to similar total learning time and total active learning time in Experiment 1 and 3b, and to a similar number of trials in Experiment 3a. Thus, the strong resemblance of the characteristics of handwriting and composition learning provides a clean comparison opportunity about the respective contribution of the graphic motor programs and the detailed visual analysis. In those three experiments, recognition performance following handwriting and composition were closely similar, both higher than typing. Consequently, there is no basis for concluding that the graphic motor programs are the source of the advantage of handwriting over typing. On the contrary, the comparable recognition performance observed after handwriting and composition would favor the visual analysis hypothesis which assumes that the detailed visual analysis is the sole source of the advantage of handwriting over typing.

To sum up, the two major empirical findings of the present set of experiments are the presence of an advantage of handwriting over typing and the lack of clear evidence of a difference between handwriting and composition. This data pattern led us to the conclusion that the handwriting advantage is due to the detailed visual analysis required for copying, rather than to the graphomotor activity per se. The latter claim is however likely to be the most debatable, as one might argue that the absence of clear evidence for a difference between handwriting and composition is due to a lack of statistical power. Evidently, referring to the recent recommendations reported by Brysbaert (2019) based on numerical simulations, the present experiments may not have sufficient statistical power to detect small size effects. Nevertheless, we reasoned that the convergence of the findings from the eight data sets (four experiments with two test measures, 4AFC and old/new) might provide stronger cumulated evidence and we aimed at quantifying it.

To that end, we ran numerical simulations (see supplementary material). Those simulations indicate that taken together, the eight data sets provide strong evidence in favor of the hypothesis that no performance difference exists between handwriting and composition, relative to the hypothesis of a medium-sized advantage of handwriting over composition (see Table 4, supplementary material). Moreover, it should be noted that given the number of participants and variability, the sensitivity to detect a small advantage of handwriting over composition would be very feeble (see Table 3, supplementary material). In other words, we cannot reject the possibility of a small advantage of handwriting over composition.

Altogether, the present experiments suggest an important contribution of the detailed visual analysis in symbol learning and provide no evidence that graphomotor training per se leads to a better encoding or helps to discriminate orientation. The present findings are in line with studies arguing for the importance of stroke units and visual analysis at the onset of learning of new graphomotor sequences (Hulstijn & van Galen, 1988; Portier et al., 1990; Swett et al., 2010), and more generally with the visual conception of letter recognition. This latter conception is supported by neuroimaging studies which assume that letter processing is carried out by a part of the left fusiform gyrus of the extrastriate visual cortex (Flowers et al., 2004; Garrett et al., 2000; James et al., 2005; Polk et al., 2002; Wong et al., 2009), and by most current models of word recognition which postulate that letter recognition is a visual process based on elementary features extraction (Coltheart et al., 2001; Grainger et al., 2008; McClelland & Rumelhart, 1981; Perry et al., 2007). The composition learning method used in the present study, can be linked to the latter models because it precisely involves a visual focus on elementary features during learning.

Although the results clearly demonstrate the impact of the detailed visual analysis, it should be noted that in natural settings, such as learning to read and spell, handwriting might constitute the most obvious and spontaneous way to promote such detailed visual analysis. Under such a view, the association between letter perception and motor activation should be interpreted as a consequence of the learning experience and not a necessary condition for encoding and recognition.

CRediT authorship contribution statement

The first and last authors designed the experiments, analyzed the data, and wrote the article. The first author collected the data of the first two experiments and part of the third experiment. The second author participated to the implementation of Experiment 3 and collected the major part of the data of this experiment. The third author wrote the supplementary material and performed the numerical simulations. The first author is a research fellow with the Belgian FRS-FNRS.

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Appendix A. Supplementary data

All data files are available at https://osf.io/x69nj/. Supplementary analyses to this article can be found online at doi:https://doi.org/10.1016/j.cognition.2020.104443.

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