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ARTICLE

Catching a CAPTCHA: the impact of variable input on the processing of emerging orthographic representations*

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Abstract

Variability inherent to handwriting has been suggested to help establish more robust letter representations than other methods (e.g., typing). The present study tests whether encoding letter strings from a novel alphabet becomes more resistant to distortion when trained with variable input. Over 5 days, participants learned an 11-character artificial alphabet in a variable handwritten format involving reading, listening and handwriting practice. Another set of 11 artificial characters served as a visual control. Before and after the training, participants completed a masked priming same–different matching task with the novel alphabet letters. The key manipulation was in the primes: the identity/unrelated primes could be presented in a printed or distorted format. Results showed identity priming in both conditions, with a stronger effect for the printed primes. These effects increased post training for experimental and visual control scripts, indicating that exposure to variable input enhances distortion resistance even without explicit training. A second experiment assessed the transposed-letter effect – another marker of orthographic processing – in the novel scripts with an unprimed same–different matching task. Results showed that the transposed-letter effect occurred similarly before and after the training for both scripts. Therefore, letter shape variability when learning to read does not seem to boost orthographic processing.

Keywords: CAPTCHA; handwriting; orthographic processing; orthographic representations; visual word recognition

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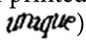
1. Introduction

Reading and writing are revolutionary inventions of human civilization and are essential communication tools in modern society. During reading, the eyes typically focus on each word in the text, often fixating only once, thereby providing a brief foveal glimpse. In this fleeting moment, skilled readers process the word, transforming the visual input into an increasingly abstract orthographic code. This code is crucial for retrieving the word's phonological, morphological and semantic properties from the mental lexicon. The present paper focuses on the emergence of orthographic processing, the critical interface between visual input and the mental lexicon. Orthographic processing serves as a vital bridge, linking the initial stages of visual perception to the more complex processing of words. It encompasses the encoding of abstract letter identities and the serial order of the letters, playing a crucial role in guiding the selection of the appropriate entries in the mental lexicon. This process is key in distinguishing orthographically similar words such as KISS from HISS or GOD from DOG (see Grainger, 2018, for review).

The process of encoding letter identities in the brain, as agreed upon broadly in the research community, involves specialized neuron layers attuned to abstract letter representations during visual word identification. A notable example is the hierarchical model of visual word recognition proposed by Dehaene et al. (2005), where specific neuron layers exhibit similar responses to different forms of the same letter (d, *d*, D or D). As reviewed by Grainger (2018), developing this level of abstraction is necessary for proficient reading and these abstract orthographic representations are both stable and resilient to visual noise – critical factors for effective reading. Notably, this ability is thought to develop relatively early after learning to read (Jackson & Coltheart, 2001). Empirical evidence supporting this view comes from masked priming experiments showing sizeable repetition priming effects with handwritten words (Gil-López et al., 2011; Qiao et al., 2010). An even more striking example of the brain's proficiency in handling distorted visual input occurs with CAPTCHAs (Completely Automated Public Turing test to tell Computers and Humans Apart; von Ahn et al., 2003). In a masked priming lexical decision task, Hannagan et al. (2012) found significant repetition priming effects with printed target words when primes were distorted in a CAPTCHA-like manner (e.g., ). Although the repetition priming effects were less pronounced than with printed primes, they were still sizeable, suggesting that the letter detectors, weathered by exposure to a wide variety of visual inputs, are quite adaptable to distortion. This adaptability allows them to respond to a broad spectrum of potential visual inputs for any given letter. In our study, we utilize the identity priming effect of CAPTCHA primes to investigate the tolerance of letter detectors to noise in the processing of letter strings for a novel – recently learned – script.

The main aim of this paper was to examine whether stable orthographic representations, resilient to distortion, can be developed in the initial stages of literacy. To explore this, we trained adult participants in a novel, artificial script over five sessions, using varied visual inputs. We opted for adults learning an artificial script instead of preliterate children to have better control over participants' prior letter knowledge and use more standardized tasks – note that in experiments with preliterate children, the tasks and procedures must be simplified enormously (Perea et al., 2016a). This approach has proven effective, akin to how children learn to read (Taylor et al., 2011; C. Vidal et al., 2017).

Employing a similar methodology, Fernández-López et al. (2021) examined the emergence of orthographic representations focusing on the encoding of letter order. In their study, participants were trained in two unfamiliar scripts, each comprising 11 BACS (the Brussels Artificial Character Sets) characters (C. Vidal et al., 2017), throughout six sessions, with each letter being assigned a phonological value. The training for one script encompassed extensive handwriting, listening and reading exercises, while the other script served as a control, concentrating solely on superficial letter recognition. The participants were tested on two aspects of orthographic processing before and after the training. First, a same–different task was administered to assess letter transposition effects, thereby evaluating the emergence of flexibility in letter position within the new script, a phenomenon known as location-invariance processing. This concept posits that letter strings evoke greater transposition effects than strings of symbols or artificial letters (Duñabeitia et al., 2012; Massol et al., 2013). Second, a target-in-string task examined the parallel processing of letter positions in a string. Prior research has shown a divergence in the accuracy functions of symbols versus letters in this task: participants tend to be more accurate when identifying centrally fixated characters in symbols, while an advantage is also observed for the exterior letters, especially the initial letter, in letter strings (Tydgat & Grainger, 2009). Fernández-López et al. (2021) observed that the findings in both tasks were strikingly similar before and after training for both the script learned by participants and the one with which they were merely visually familiarized. They suggested that more robust orthographic representations are required to distinguish orthographic processing from the processing of other visual symbols – particularly regarding location invariance and position-specific processing. Nonetheless, their study primarily examined the emergence of location-invariance and location-specific processing in letter strings of the newly trained script without directly examining the development of the encoding of letter representations. Our study seeks to address this gap in the literature.

One effective strategy to develop more stable letter representations involves increasing the variability of the visual input. This approach was examined in a study by Li and James (2016), which focused on 5-year-old children learning four Greek letters previously unfamiliar to them. The children were trained using either variable or invariable input coupled with either visual-motor or visual-auditory training methods. Li and James (2016) found that variable input, irrespective of the training type, enhanced the children's ability to categorize a letter correctly in the subsequent testing phase. They argued that exposure to only a singular form of a letter (e.g., a) would make it challenging for a learner to recognize that ɑ and a belong to the same abstract letter unit. However, through repeated exposure to various letter forms within the same context, learners can develop a more robust sense of letter invariance.

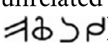
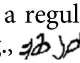
In the present paper, we examined whether orthographic representations would emerge after the reading–learning process rich in variability. Specifically, we primarily focused on the encoding of letter identities. Our methodology was based on the training protocol used by Fernández-López et al. (2021) but with two significant modifications. First, to introduce variability in the training input, we presented the learning materials in four different handwritten fonts, as opposed to the printed BACS2serif font used previously (refer to Table 1 for details). Second, to assess whether the newly formed orthographic representations could withstand distortion, we conducted the masked priming same–different task introduced by Norris and Kinoshita (2008) and Kinoshita and Norris (2009). In this task, primes were either identical or unrelated to the target and were presented in either a regular, printed format (e.g., ) or a distorted, CAPTCHA-like format (e.g., ). Notably, the repetition priming effects potentially observed in this task – even for familiar alphabetic stimuli – are considered to be prelexical, indicating that any observed

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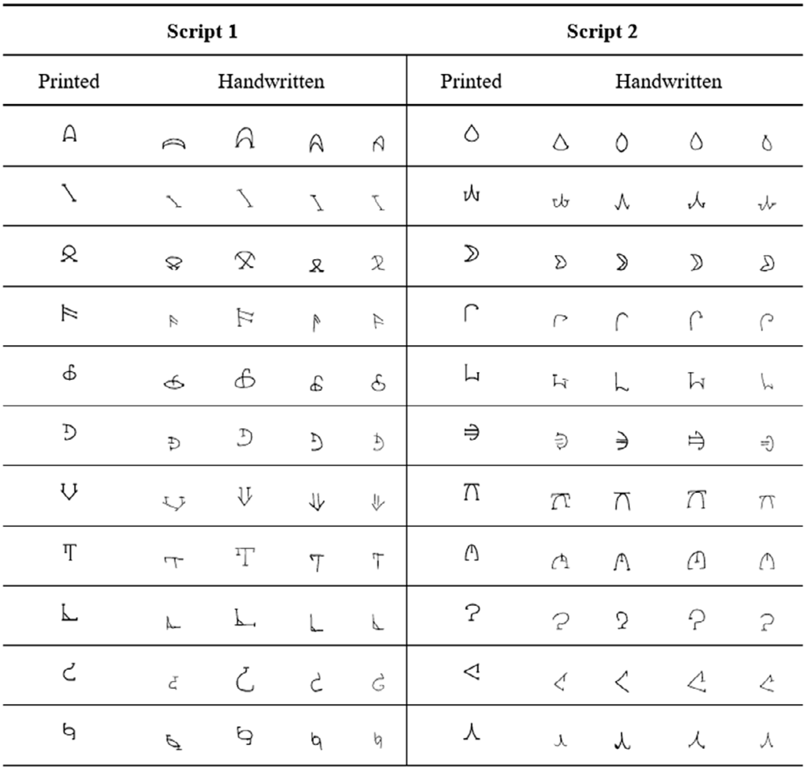
Table 1. Letters from Scripts 1 and 2 in printed BACS2serif and handwritten versions



effects would primarily reflect bottom-up activation from the visual input to the letter detectors (Kinoshita et al., 2018; Perea et al., 2016b).

If the variability in training materials indeed bolsters the emergence of a greater tolerance to noise in the evolving detectors for letter identities, we predict an increased masked repetition priming effects post training, particularly for the printed format, but, crucially, also for the CAPTCHA-like primes, only for the alphabet that participants learned to read. Conversely, the lack of differences in repetition priming effects between the trained alphabet and the visual control would imply that the obtained priming effects are not uniquely orthographic but rather stem from greater visual familiarity with the script. Additionally, as a secondary objective, we explored the encoding of letter order in this new setup using the same task employed by Fernández-López et al. (2021) – the specific details will be discussed in the context of Experiment 2.

2. Experiment 1: the emergence of abstract letter representations

2.1. Methods

The analysis, exclusion criteria and sample size justification were preregistered at https://aspredicted.org/PLZ_FNB. The study was approved by the local ethical committee.

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2.2. Participants

Participants were 28 native Spanish speakers (mean age = 20.69 years, SD = 1.75) with normal or corrected-to-normal vision and reported no language-related or learning disorders. All participants gave informed consent and were given monetary compensation upon completing the experiment.

2.3. Materials and design

In the experiment, we used two novel scripts from previous research (Fernández-López et al., 2021), available at https://osf.io/um6rw/?view_only=7d4754bbb5f445adb5e34530162ba552. Each script is a different subgroup of the BACS alphabet (C. Vidal et al., 2017) and each is comprised nine consonants and two vowels. They were matched in visual complexity and other visual properties by design, thus avoiding any confounds. Each participant learned one script via print-to-sound training, to establish grapheme–phoneme associations (i.e., experimental script). In contrast, learning the other script referred to the visual familiarization with the characters (i.e., control script). The use of the script across participants was counterbalanced. Four different handwritten fonts were created using the Calligraphr online app (www.calligraphr.com), to create the variability in the input. The complete scripts and their handwritten versions can be seen in Table 1.

2.3.1. Training

Learning to read. As mentioned at the beginning of this subsection, the learning materials were identical to those of Fernández-López et al. (2021), with one crucial difference: instead of the capital letters of BACS2serif font (C. Vidal et al., 2017), they were presented in a handwritten font. Within each character string, only one font was used. The use of different fonts was pseudorandomized across items.

The training in the experimental script was done as follows. On the first day, participants familiarized themselves with the grapheme–phoneme correspondences of the experimental script. They were presented with graphemes of the novel script and their corresponding phonemes. They were asked to read, listen and hand-copy them on a piece of paper until they felt confident in remembering the associations. On Day 2, they briefly reviewed the associations and completed three read-aloud tasks involving 12 sequences of four and five characters. They also completed three write-down tasks, which consisted of listening and writing down another four- and five-character-long sequences. On Day 3, they completed the same tasks with six- or seven-character-long sequences, and on Day 4, they completed the same set of tasks with eight-character-long sequences and then with six-, seven- and eight-character-long sequences.

Visual familiarization. To familiarize the participants with the control script's visual form, they were presented with the list of all control script characters on the first day. They were asked to try to remember them. To practice the control script, we administered a character count and detection tasks on Days 2, 3 and 4.

Character count task. In the character count task, a fixation point appeared on the screen for 500 ms, substituted by a character string for a maximum of 2,000 ms or until response. Participants were asked to press 'yes' only if the character string that appeared on the screen contained three or more nonalphabetical symbols.

Character detection task. In the character detection task, a character from the untrained script, which acted as a probe, appeared on the screen for 1,000 ms, followed by a pattern mask (####) for 500 ms. The mask was then substituted by a

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target, a string of characters from the untrained script that had an equal length as the mask. It stayed on the screen until response or until a timeout of 2,000 ms. The participants were instructed to respond 'yes' if the probe appeared in the target or 'no' if it did not. The length of the character string in both Character count and Character detection tasks corresponded to the length of the string in the training on that day (i.e., if the training was on four and five-character strings, so were the visual familiarization tasks). In 75% of the trials (27 out of 36), the BACS characters were presented in a handwritten font – in the remaining 25%, the characters were presented in the standard BACS font, to ensure that participants were exposed to the typical version of the letters in the control script. The use of the four handwritten fonts was pseudorandomized across trials.

2.3.2. Testing task – masked priming same–different task

Materials. The probes, primes and targets were four-consonant strings composed of characters belonging to one of the scripts, thus creating two versions of the task, one for each script. Characters were never repeated within a single string. Three hundred and twenty probe-target pairs were created, 160 belonging to the 'same' condition (probe and target were identical) and 160 to the 'different' condition (probe and target consisted of entirely different characters). Half of the primes were distorted similar to CAPTCHAs (von Ahn et al., 2003), while the other half was presented in a regular printed format. CAPTCHA items were generated using Python script (Python version 3.6.6; packages: pandas [version 1.1.5.], PIL [version 8.0.1.]). This yielded a 2 × 2 × 2 design (same–different strings × identity-unrelated probe × printed-distorted prime). Four lists, each comprising 320 trials, were created following the Latin square design. In addition, a practice list with the same criteria, containing 24 trials, was generated.

Procedure. The task was programmed using PsychoPy3 Builder v2020.2.10 (Peirce et al., 2019). Like the standard masked same–different paradigm, the trial sequence began with a 500 ms presentation of a fixation cross at the center of the screen. It was followed by a probe and mask appearing together for 1,000 ms. The mask consisted of four hashtags and was positioned under the probe. Subsequently, the prime was presented in the location of the mask for 50 ms, which was then replaced by the target in isolation until a button press or a 2,000 ms timeout (see Figure 1). The target could be either the same letter string as the probe ('same' trials) or a different letter string ('different' trials). To prevent perceptual continuity, the prime was in a smaller size than the target. Participants were instructed to respond as accurately and as quickly as possible whether the two-character strings were the same or not. The session lasted ~18 min.

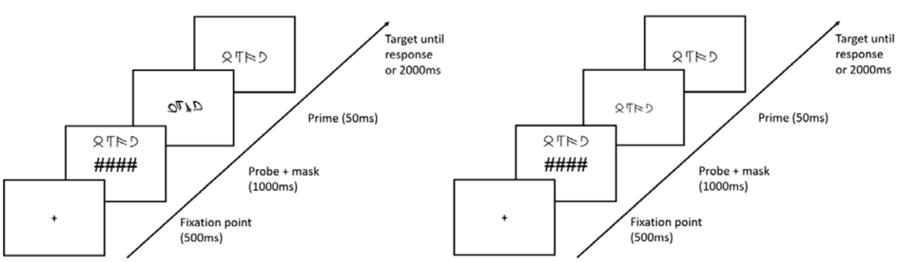

Figure 1. Illustration of the masked priming same–different task with the distorted (CAPTCHA) prime on the *left* and the printed prime on the *right* for 'same' trials.

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2.4. Overall procedure

The experiment took place in a quiet laboratory setting over five consecutive workdays. It consisted of the pre-training, training and post-training phases. On the first day, participants completed the pre-training phase: they were administered masked priming same–different task and the regular same–different task (described in Experiment 2) in both Script 1 and Script 2. The order of the tasks was counterbalanced. Then, they were familiarized with the experimental and control scripts. Half of the participants learned Script 1 and half learned Script 2. On Days 2, 3 and 4, they were trained on letter strings of increasing length (four to eight characters) for the experimental script and they completed the visual familiarization tasks for the control script (detailed description below). On Day 4, in addition to the training on eight-character letter strings, another round of training with strings of mixed length (six, seven and eight characters) was completed, to maximize learning. On the last day, they were first administered a test consisting of one read-aloud exercise and one listening and writing exercise. After passing the test with a minimum of 84% correct responses (20 correct responses out of 24 in reading and writing), they completed the post-training phase, which consisted of masked priming same–different task and the regular same–different task in the script they were trained on. For a graphic depiction of the training, see Figure 2. For more details on the procedure, see Fernández-López et al. (2021).

2.5. Data analysis

Table 2 shows the average RTs and accuracy. In the preregistered statistical analysis, the critical dependent variable was RT. All RTs shorter than 250 ms and incorrect responses were removed from the analyses (8.53% of data points were removed). The analysis focused on the 'same' trials (where the probe was identical to the target) because that is where the priming effect can be observed. We also conducted a parallel analysis of the accuracy data – this analysis was not preregistered (see the Appendix). All data and data analysis scripts are available at https://osf.io/85dmp/.

We ran Bayesian linear mixed models to analyze the data using the *brms* package (Bürkner, 2017, 2018) in R (R Core Team, 2021). In the pre-registration, we chose this option over frequentist models to mitigate convergence issues, allowing for the maximal random-effect structure without simplification (see Barr et al. (2013), for a discussion of the risks of simplifying the structure of the design). Phase, script, prime relatedness and prime distortion, and their four-way interaction were contrast-coded as fixed effects – these effects were zero-centered: *identity* versus *unrelated* (–0.5 and as 0.5), *pre-training* versus *post-training* (–0.5 and as 0.5), *trained* versus *untrained* (–0.5 and as 0.5) and *captcha* set versus *printed* set (–0.5 and as 0.5). We used the maximal random structure both for participants and items.[1] We used a shifted log-normal distribution for the reaction time data. The priors for the response time (RT) data were weakly informative: Normal ($\mu = 0, \sigma = 10$) for the intercept and Normal (0, 1) for each

[1]Brms_captcha_rt_model <- brm(data = captcha_data_rt, rt ~ pre_post_c * trained_c * prime_relatedness_c * prime_distortion_c + (1 + prime_distortion_c * pre_post_c * trained_c * prime_relatedness_c| participant) + (1 + prime_distortion_c * pre_post_c *prime_relatedness_c | item), warmup = 1000, iter = 5000, chains = 4, family=shifted_lognormalsample_prior = T, prior = priors, save_all_pars = T, control = list(adapt_delta = 0.95), cores = 4).

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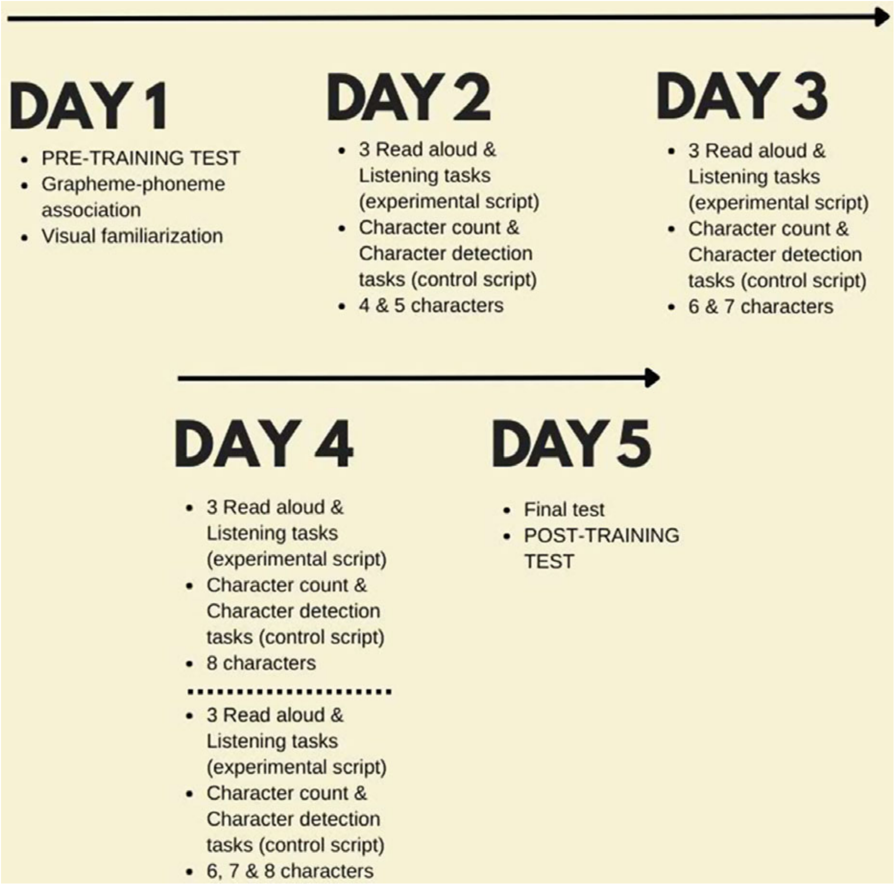

Figure 2. Scheme of the experiment procedure over 5 days.

Table 2. Masked priming same–different task: mean correct reaction times (in milliseconds) and accuracy (in parentheses) across conditions

		Pre-training		Post-training	
		Trained	Untrained	Trained	Untrained
Identity	Captcha	613 (7.7%)	625 (7.7%)	538 (6.6%)	547 (8%)
	Printed	570 (4.3%)	581 (4.4%)	500 (3.9%)	500 (5%)
Unrelated	Captcha	638 (9.8%)	650 (11%)	576 (11.3%)	575 (11.1%)
	Printed	607 (8.5%)	628 (6.4%)	552 (9.7%)	552 (11%)
Priming effect	Captcha	25 (2.1%)	25 (3.3%)	38 (4.7%)	28 (3.1%)
Priming effect	Printed	37 (4.2%)	47 (2%)	52 (5.8%)	52 (6%)

of the fixed effects/interactions and SD parameters.[2] For the covariance matrix of random effects, we had a regularization of 2.

[2]As a further check that the present findings were not affected by the choice of priors done in the preregistration, we also conducted the analyses using the default prior from *brms* package. They produced virtually the same estimates.

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The model was fitted using four chains with 5,000 iterations (1,000 as warmup). We consider an effect credible if the 95% credible interval (CrI) estimated from the posterior distribution does not contain zero. Simple test effects in case of evidence for interactions were made using the *emmeans* package (Lenth, 2021).

2.6. Results

The results of the reaction time data showed evidence of a main effect of phase (*b* = –0.22, Estimation Error = 0.05, 95% CrI [–0.31, –0.13]) where RTs were faster after training (542 ms) than before (614 ms). We also found evidence of an effect of prime-target relatedness (*b* = 0.13, Estimation Error = 0.01, 95% CrI [0.10, 0.15]) with faster responses for identity targets (559 ms) compared to unrelated targets (597 ms) and an effect of prime distortion (*b* = –0.12, Estimation Error = 0.01, 95% CrI [–0.14, –0.09]) with advantage for targets preceded by printed primes (561 ms) than distorted primes (595 ms). Prime relatedness interacted with phase (*b* = 0.04, Estimation Error = 0.01, 95% CrI [0.02, 0.07]). Unpacking this interaction showed a larger masked repetition priming effect in the post-training phase (42 ms; *b* = -0.15, 95% CrI [–0.17, –0.12]) than in pre-training (33 ms; *b* = –0.10, CrI [–0.13, –0.08]). Prime relatedness also interacted with prime distortion (*b* = 0.08, SD = 0.02, 95% CrI [0.04, 0.11]). This interaction revealed greater repetition priming effects for targets preceded by printed (47 ms; *b* = –0.17, 95% CrI [–0.19, –0.13]) than distorted primes (29 ms; *b* = –0.09, 95% CrI [–0.11, –0.06]). Figure 3 depicts posterior distributions from the estimates in the model. As shown in Figure 3, we found no evidence of the effects related to the script (either trained vs. untrained) or its interactions with the other factors.

The analysis of the accuracy data showed essentially the same general pattern as the reaction time analyses (see the Appendix for details).

Thus, we found a stronger repetition priming effect after training than before training. Critically, this increase in the priming effect cannot be attributed to orthographic processing, as a similar pattern was observed for both the script that

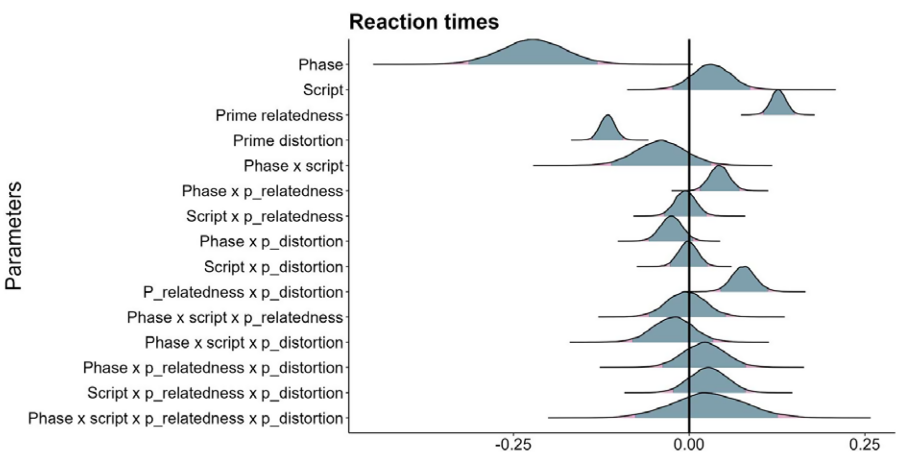

Figure 3. Ninety-five percent and 100% highest density intervals from the Bayesian linear mixed-effects model for the reaction times in the masked priming same–different task.

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participants learned to read and the script with which they were merely visually familiarized. In addition, we found a stronger repetition priming for the intact primes than for the distorted primes; again, this effect was similar for the trained and untrained scripts.

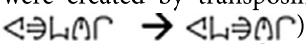
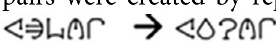
3. Experiment 2: the emergence of location-invariant processing with variable visual input

A secondary goal of the present paper was to test whether variability in input could enhance the flexibility of letter position encoding in orthographic representations. The underlying rationale was that increased variability in letter forms might influence how letter order is encoded in the novel-trained script. To this end, we implemented a same–different task parallel to the one used by Fernández-López et al. (2021, Experiment 1). As discussed in the Introduction, they found a consistent pattern of transposed-letter effects in the new script, both before and after training. This pattern was parallel for trained and visual control scripts. We aimed to reassess these results under conditions where the visual input included variability in letter forms to understand the impact of these variations on the transposed-letter effect. Should variability in visual input facilitate the emergence of orthographic processing, we anticipated an increase in the transposed-letter effect in the post-training test compared to the pre-training test, reflected in more errors in the transposed compared to replaced letter condition. However, this increase was expected only for participants trained to read the script. Conversely, if this added variability does not impact the development of orthographic processing regarding letter-position encoding, we would expect a similar pattern of transposed-letter effects for both the trained and untrained scripts like that reported by Fernández-López et al. (2021).

3.1. Methods

Participants, overall training procedure and materials for the training were identical to Experiment 1. The testing task differed, as described below.

3.1.1. Testing task – same–different task

Materials. A separate set of items was created for each of the two scripts. Each set consisted of 240 probe-target five-character consonant string pairs, displayed in 15pt BACS2serif font (C. Vidal et al., 2017). All character strings were composed of non-repeated letters. One hundred and twenty items belonged to the 'same' condition and another 120 belonged to the 'different' condition. In the 'different' condition, 60 pairs were created by transposing two adjacent letters (e.g., 1-2-3-4-5 → 1-3-2-4-5; ) and 60 pairs were created by replacing two adjacent letters (e.g., 1-2-3-4-5 → 1-6-7-4-5; ). The proportion of transpositions/replacements was the same in all letter locations. To counterbalance the probe–target pairs, we created two lists for each script. For the practice phase, we created eight 5-consonant string pairs for each script with the same criteria. Participants were instructed to press 'yes' if the two strings were the same or 'no' if they did not. They were encouraged to be as quick and as accurate as possible. The session lasted ~18 min. The task was programmed using DmDX software (Forster & Forster, 2003).

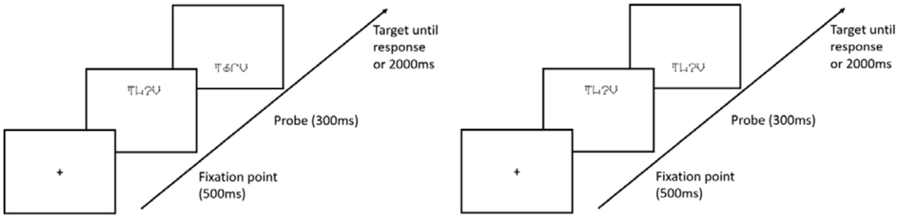


Figure 4. Illustration of the same–different task with the 'same trial' on the *left* and the 'different' trial on the *right.*

Table 3. Same–different task: mean correct reaction times (in milliseconds) and accuracy (in parenthesis) across conditions

		Pre-training		Post-training	
		Trained	Untrained	Trained	Untrained
Different	Transposed	659.96 (45%)	704.10 (46%)	620.77 (41%)	613.62 (43%)
	Replaced	630.08 (27%)	675.36 (27%)	569.62 (24%)	570.24 (24%)
Same		584.44 (8%)	617.93 (10%)	539.74 (8%)	530.25 (9%)

Procedure. The task followed the same design as in Fernández-López et al. (2021). In each trial, a fixation point appeared in the center of the screen for 500 ms. Then, it was substituted by a probe positioned 3 mm above the center of the screen for 300 ms. Next, the target appeared 3 mm below the center of the screen and remained at display until response or until a timeout of 2,000 ms. See Figure 4 for the illustration of the procedure.

3.2. Data analysis

Table 3 shows the average accuracy and RTs only for the correct items. Following the preregistered statistical analysis, the only dependent variable was accuracy. We also analyzed the reaction times in a non-preregistered analysis (see the Appendix). We analyzed only the 'different' trials because that is where the critical manipulation lies (i.e., transposed-letter vs. replacement-letter pairs). All data and analysis scripts are available at https://osf.io/85dmp/.

We analyzed the accuracy data using Bayesian generalized mixed models. The fixed effects were a phase (pre- vs. post-training), training (trained vs. untrained [visually familiarized]) and probe–target relationship (transposed vs. replaced). We used the maximal random factor structure for participants and items. They were contrast-coded as zero-centered fixed effects: *pre-training* versus *post-training* (–0.5 and as 0.5), *trained* versus *untrained* (–0.5 and as 0.5) and *transposed* set versus *replaced* set (–0.5 and as 0.5). For the fits, and due to the binary nature of the responses (1 denoting a correct response and 0 an incorrect response), we used the Bernoulli distribution with a logit link. The priors and model fitting were identical to the masked priming same–different task. Again, we considered an effect as credible where the 95% CrI estimated from the posterior distribution did not contain zero. The *emmeans* package (Lenth, 2021) was used to unpack significant interactions.

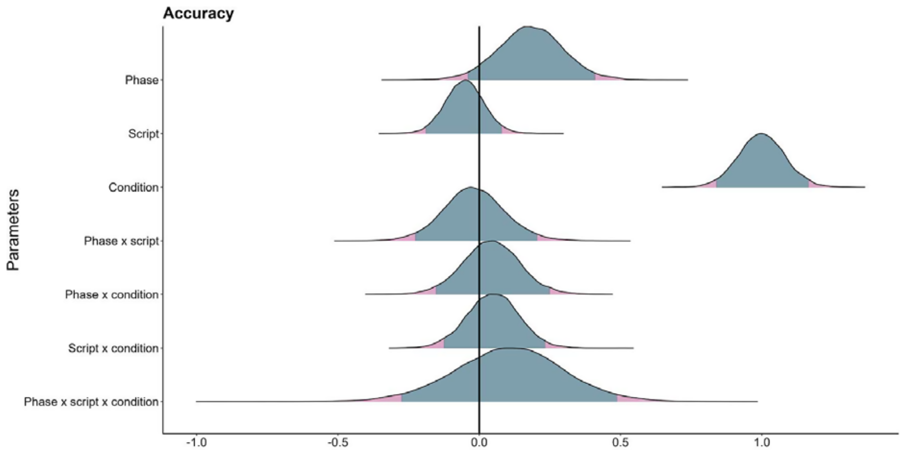


Figure 5. Ninety-five percent and 100% highest density intervals from the Bayesian generalized mixed-effects model for accuracy in same–different task.

3.3. Results

The results of the accuracy data showed evidence of an effect of the probe–target relationship (b = 1.00, 95% CrI [0.84, 1.16]) where the error rate in the replaced condition was lower compared to the transposed condition (43.75% vs. 25.5%). We did not find any signs of the other effects or interactions (Figure 5 depicts the posterior effects estimates from the model).

While not preregistered, the analysis of the RTs replicated the transposed-letter effect. Moreover, phase also affected the reaction times, with faster RTs after the training, and the interaction of the probe–target relationship and phase showed a stronger effect after the training (see the Appendix for details).

Thus, we found the typical transposed-letter effect: participants' responses were more accurate for replacement-letter pairs than transposed-letter pairs. Critically, as also occurred in the Fernández-López et al. (2021) experiment, the magnitude of this effect was similar before and after the training. Also, it was similar for both the trained script and the visual control script. In other words, adding variability to the letter shapes in the training phase did not modulate how participants encoded the position of the characters in the letter strings.

4. General discussion

In the present experiments, we examined whether the variable visual input influences the development of two fundamental components of orthographic processing: the encoding of letter identity and letter position. The underlying premise was that exposure to varied visual input would facilitate the formation of more robust letter representations, as shown by Li & James (2016). To test this hypothesis, we trained participants in an artificial script, using handwritten versions, until they attained proficiency in reading, listening and handwriting. Additionally, we introduced a second set of novel letters as a visual control to better assess the specific impact of reading and handwriting training. For the control script, participants were only familiarized with their visual forms without the associated reading and handwriting

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training. In Experiment 1, participants completed a masked priming same–different task both before and after training. This task involved identity versus unrelated priming conditions, employing both printed and distorted (CAPTCHA-like) primes. The aim was to assess the tolerance of the newly learned letters against visual distortion. Specifically, the emergence of a greater repetition priming effect with CAPTCHA-like items after training in the novel script would suggest that these representations are resilient to distortion. In Experiment 2, we shifted our focus to determine whether the novel characters had been internalized as abstract orthographic representations by examining whether training induced a more flexible encoding of letter order – an index of orthographic processing (Grainger, 2018). To assess this, we employed a same–different task comparing transposed-letter versus replacement-letter pairs. Here, an increased transposed-letter effect observed post training would indicate effective orthographic processing. This is supported by previous findings, which suggest that letter strings typically exhibit stronger transposition effects than strings of non-letter symbols (Duñabeitia et al., 2012; Massol et al., 2013).

The results of the masked priming same–different task (Experiment 1) revealed several key findings. First, we found that even before any training, distorted primes (such as CAPTCHA) could produce repetition priming effects. This suggests that the cognitive system of adult readers can handle a certain degree of variability in the letters of a novel script, even when they are still entirely unfamiliar. This finding aligns with and extends previous research indicating that visually variable primes, including handwritten and CAPTCHA primes, aid in word processing (Gil-López et al., 2011; Hannagan et al., 2012; Qiao et al., 2010). However, it is important to note that these earlier studies employed tasks like lexical decision (Gil-López et al., 2011; Hannagan et al., 2012) and semantic categorization (Qiao et al., 2010), which might involve top-down processes aiding in the integration of primes and targets (see Vergara-Martínez et al., 2015). In contrast, the masked priming same–different task primarily targets prelexical processing, minimizing the influence of top-down information (Norris & Kinoshita, 2008; Perea et al., 2016b). Therefore, our results demonstrate that distorted primes can facilitate the processing of letter strings without lexical feedback.

Second, we found that the repetition priming effect was greater in the post-training phase, indicating that participants' familiarity with the novel letters increased over the training sessions, yielding a sizable processing advantage. Notably, this boost in the priming effect was observed both for the experimental and visual control scripts. Thus, the enlarged repetition priming effect in the post-training phase should be attributed more to heightened visual familiarity with the input rather than the development of orthographic representations specific to the script participants learned to read.

Therefore, Experiment 1 uniquely demonstrated that distorted CAPTCHA primes can be effectively normalized even in the absence of top-down influences. This finding suggests that after training, participants had become more attuned to the visual forms of the characters. In addition, participants could quickly develop stable visual representations of the characters, which remained tolerant to input variability. Crucially, the absence of differences in the results between the script that participants learned to read and write, and the script with which they were only visually familiarized implies two key points: (1) participants were able to construct resilient representations of the novel characters even when there were no connection to phonological information and (2) these representations are not orthographic in nature. The results from Experiment 2 further corroborate our initial conclusion. This experiment aimed to assess the development of location-invariance processing.

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We employed a same–different task to compare participants' accuracy in responding to transposed-letter versus replaced-letter pairs, measuring the transposed-letter effect. The findings revealed similar transposed-letter effects for the trained and control scripts, consistent in both the pre- and post-training phases. This extends the observations of Fernández-López et al. (2021) to a context with high variability in visual input. Consequently, our study suggests that learning to read and write in a new script does not necessarily lead to a rapid emergence of location-invariant processing. One remaining question for further experimentation is whether fully consistent character exposure could modulate the pattern of findings (e.g., always presenting the same pristine font on the screen and having participants type rather than handwrite during the learning phase of the trained script, versus presenting handwritten fonts and having participants handwrite during the learning phase). However, as stated above, the experiments of Fernández-López et al. (2021), in which participants were always exposed to a pristine font, also reported the absence of orthographic processing, as indicated by the lack of differences in location-invariance and location-specific processing in the pre- and post-training phases in the experimental and control scripts.

All in all, the results of our experiments provide valuable insights for understanding the process of learning to read in a novel script. Despite achieving fluency in reading and writing the new script over five training sessions, participants did not sufficiently develop orthographic representations in terms of both letter identities and letter order. A possible explanation for this pattern might be that the intensity of training in a novel script cannot replicate the extensive exposure and experience with letters and letter strings typically received by children when learning to read and write. The development of children's reading skills often involves substantial visual familiarization with letters, even before formal reading instruction begins, and the association of graphemes and phonemes with words. Thus, the emergence of orthographic processing likely occurs progressively through print exposure (Gomez et al., 2021; Mano & Kloos, 2018). It is possible that both training protocols provided enough information to perform the post-training tasks (especially bearing in mind that transposed-letter effects emerge also with nonalphabetic symbols), but not enough to establish more robust representations. Crucially, the absence of specific patterns typical for language in our experimental letter strings (e.g., frequent letter co-occurrences acquired via statistical learning) may have impacted our results. Such patterns are crucial in orthographic processing and visual word recognition (e.g., Chetail, 2017; Fernández-López & Perea, 2023; Lelonkiewicz et al., 2020, 2023; Y. Vidal et al., 2021). For instance, Chetail (2017) found that adults developed sensitivity to the frequency of bigrams in artificial character streams after brief exposure, regardless of learning grapheme–phoneme associations. Fernández-López and Perea (2023) extended this to the encoding of character order, demonstrating that participants also became attuned to the order of characters in frequently occurring sequences. This evidence suggests that a certain level of regularity, such as letter co-occurrences, is necessary for the cognitive system to effectively modulate letter position encoding.

Our findings can also be interpreted as revealing an intermediary phase in the progression from the general processing of visual objects by the visual system to the specialized processing of orthography. Since reading is a relatively recent development in human history, its foundational representations and processes likely originate from basic visual perception mechanisms. This notion aligns well with the Neuronal Recycling Hypothesis (Dehaene & Cohen, 2007), which posits that the brain repurposes existing neural pathways for new tasks, such as reading. Recent research by Y. Vidal et al. (2021) builds upon this hypothesis, investigating if the bigram frequency effect, typically associated with orthographic material (e.g., Binder et al., 2006; Chetail, 2015; Lochy et al., 2018; Vinckier et al., 2007), could also be observed in non-orthographic stimuli. They discovered that participants were sensitive to co-occurrence patterns across various visual objects, suggesting that mechanisms used in visual word recognition might apply more broadly. This finding supports the idea that letter and word-specific processing evolves from pre-existing visual processing systems as familiarity with orthographic material increases.

Central to this discussion is the role of the Visual Word Form Area (VWFA) in the left ventral occipitotemporal cortex, which is crucial for rapid word recognition in skilled reading (Cohen et al., 2000; Cohen & Dehaene, 2004; Lochy et al., 2018; Vinckier et al., 2007). Neurons in this area become tuned to recognize orthographic regularities, showing increased activation when processing letter sequences resembling words (Binder et al., 2006; Cohen et al., 2002; Vinckier et al., 2007; but see Brem et al., 2006; Tagamets et al., 2000, for alternative views). Developmental studies indicate that VWFA specialization is influenced by early reading experiences (Brem et al., 2010; Dehaene-Lambertz et al., 2018; Eberhard-Moscicka et al., 2015; Lochy et al., 2016; Maurer et al., 2006; Schlaggar & McCandliss, 2007). In this line, recent work underscores the importance of teaching methods, particularly those that automate grapheme–phoneme connections rather than relying on the visual memorization of whole words, in developing advanced reading skills and preventing reading disabilities (Castles et al., 2018; van de Walle de Ghelcke et al., 2020). Considering these findings, models of reading development should incorporate this transitional stage where letters evolve from mere visual objects to recognized orthographic entities. Examining this incipient phase may have significant implications for instructional approaches in early literacy education, thus emphasizing the need for strategies that support this fundamental aspect of learning to read.

5. Conclusion

In sum, our experiments examined if orthographic processing, defined as the encoding of letter identities and their positions (Grainger, 2018), could rapidly emerge when learning to read a novel script with visually variable input. Although participants achieved fluency in reading and writing the new script, the evidence from our study does not support the hypothesis of rapid development of orthographic processing under these conditions – a similar pattern of results emerged with a visual control script. Critically, our findings also revealed that exposure to variable visual input did foster the formation of resilient character representations, demonstrating high resistance to distortion. This resilience, however, appears to be rooted in visual cognitive mechanisms rather than the development of orthographic representations.

Data availability statement. Data and analysis code are available at https://osf.io/85dmp/; training materials are available at https://osf.io/um6rw/?view_only=7d4754bbb5f445adb5e34530162ba552.

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Competing interest. The authors declare no competing interests.

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A. Appendix

Supplementary non-preregistered analyses.

A.1. Experiment 1: the emergence of abstract letter representations

A.1.1. Data analysis – accuracy

We ran Bayesian generalized linear mixed models to analyze the data using the *brms* package (Bürkner, 2017, 2018) in R (R Core Team, 2021). Phase, script, prime relatedness and prime distortion, and their four-way interaction were contrast-coded as fixed effects – these effects were zero-centered: identity versus unrelated (–0.5 and as 0.5), pre-training versus post-training (–0.5 and as 0.5), trained versus untrained (–0.5 and as 0.5)

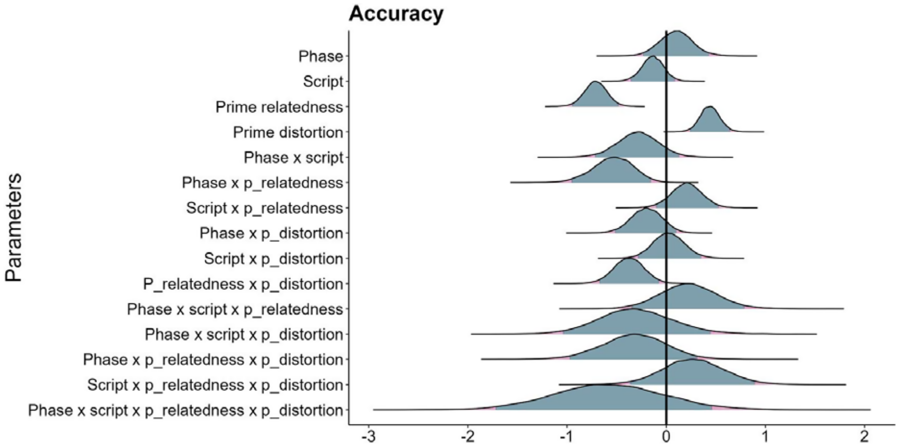

Figure A1. Ninety-five percent and 100% highest density intervals from the Bayesian generalized mixed effects model for the accuracy in the masked priming same–different task.

and captcha set versus printed set (–0.5 and as 0.5). We used the maximal random structure both for participants and items. We used the Bernoulli distribution with a logit link. The priors for the RT data were weakly informative: Normal (μ = 0, σ = 10) for the intercept and Normal (0, 1) for each of the fixed effects/ interactions and SD parameters. For the covariance matrix of random effects, we had a regularization of 2.

The model was fitted using four chains with 5,000 iterations (1,000 as warmup). We consider an effect credible if the 95% CrI estimated from the posterior distribution does not contain zero. Simple tests effects in case of evidence for interactions were made using the *emmeans* package (Lenth, 2021).

A.1.2. Results

The results of the accuracy data mimicked the same pattern of priming effects as the latency data (see Figure A1). We found evidence for an effect of prime-target relatedness (b = –0.71, Estimation Error = 0.12, 95% CrI [–0.94, –0.48]), with target words being responded more accurately when preceded by an identity prime than an unrelated prime (5.95% vs. 9.85% error rate), and also an effect of prime distortion (b = 0.44, Estimation Error = 0.10, 95% CrI [0.24, 0.64]), where printed primes yielded more accurate responses than distorted primes (6.65% vs. 9.15% error rate). Moreover, prime-target relatedness interacted with phase (b = –0.54, Estimation Error = 0.21, 95% CrI [–0.96, –0.16]): the identity priming effect was smaller after the training (4.9% error rate; b = 0.44, 95% CrI [0.15, 0.73]) than before training (2.9% error rate; b = 0.98, 95% CrI [0.67, 1.31]) (see Table 2). Prime-target relatedness also interacted with distortion (b = –0.38, Estimation Error = 0.15, 95% CrI [–0.68, –0.08]), where identity priming was larger when the prime was in printed format (4.5% error rate reduction; b = 0.90, 95% CrI [0.61, 1.19]) than in distorted format (3.3% error rate reduction; b = 0.52, 95% CrI [0.27, 0.78]). Finally, we found no evidence of the effect of phase or the other interactions (see Figure A1).

A.2. Experiment 2: the emergence of location-invariant processing with variable visual input

A.2.1. Data analysis – reaction times

We analyzed the data using Bayesian linear mixed model. The fixed effects were phase, training, transposed/ replaced letters and their interaction, with the maximal random structure for participants and items. We used shifted log-normal distribution. The priors and model fitting were identical to the masked priming same–different task. Again, we consider an effect as credible where the 95% CrI estimated from the posterior distribution did not contain zero. The *emmeans* package (Lenth, 2021) was used to unpack significant interactions.

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A.2.2. Results

We found evidence for an effect of phase (see Figure A2), with an advantage in post-training compared to pre-training (667 ms vs. 593 ms), (b = –0.11, Estimation Error = 0.03, 95% CrI [–0.16, –0.06]). Moreover, transposed letter effect emerged independently (b = –0.05, Estimation Error = 0.01, 95% CrI [–0.07, –0.04]), with transposed-letter condition being slower compared to replaced (649 ms vs. 611 ms). The effect emerged also in interaction with phase (b = –0.03, Estimation Error = 0.01, 95% CrI [–0.05, –0.00]), with stronger effect emerging after the training (pre-training: 29.31 ms; b = 0.04, 95% CrI [0.02, 0.06] vs. post-training: 47 ms; b = 0.07, 95% CrI [0.05, 0.09]). Phase also interacted with script (b = –0.07, Estimation Error = 0.03, 95% CrI [–0.12, –0.01]), where facilitation was strong in pre-training but was lost in post-training (44 ms; b = –0.06, 95% CrI [–0.11, –0.02] vs. –3 ms; b = 0.01, 95% CrI [–0.03, 0.04]).

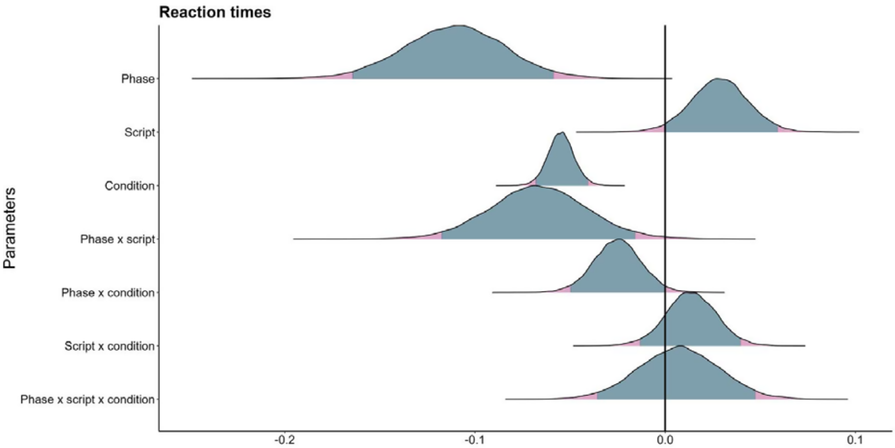

Figure A2. Ninety-five percent and 100% highest density intervals from the Bayesian linear mixed effects model for reaction times in same–different task.

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