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Research report

# Procedural and declarative knowledge of word recognition and letter decoding in reading an artificial script

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## Abstract

In a previous study [Cogn. Brain Res. 16 (2003) 325], we found that letter knowledge did not evolve from implicit training on whole-word recognition in an artificial Morse-like script, although the participants were adults, experienced in alphabetical reading. Here we show minimal conditions in which letter knowledge may evolve in some individuals from training on whole-word recognition. Participants received multi-session training in reading nonsense words, written in an artificial script, in which each phoneme was represented by two discrete symbols. Three training conditions were compared: alphabetical whole words with letter decoding instruction (Explicit), alphabetical whole words (Implicit), and non-alphabetical whole words (Arbitrary). Subjects were assigned to training either on the explicit and arbitrary or on the implicit and arbitrary conditions. Our results show that: (a) Letter-decoding knowledge evolved implicitly from training on alphabetical whole-word recognition, in some individuals. However, (b) a clear double dissociation was found between effectively applied implicit letter knowledge and declarative letter knowledge. (c) There was no advantage of the implicitly derived over the explicitly instructed letter knowledge. (d) Long-term retention was more effective in the explicit compared to the arbitrary condition. (e) Word-specific recognition contributed significantly to performance in all three training conditions, i.e. even under conditions that presumably afford advantage for word segmentation. Altogether, our results suggest that both declarative and procedural knowledge contributed to letter decoding as well as to word-specific recognition performance. Moreover, a greater dependency on declarative knowledge may not be an inherent characteristic of word-specific recognition, but rather that both letter decoding and word-recognition routines can become proceduralized given sufficient practice.

*Theme:* Neural basis of behavior
*Topic:* Learning and memory: systems and functions

*Keywords:* Implicit learning; Reading; Skill acquisition; Transfer

## 1. Introduction

There is an ongoing debate about the critical necessity of explicit instruction of phonological decoding rules for the acquisition of reading skills [29]. The argument in support of this notion is based on the assumption that beginning readers depend on letter segmentation and on phonological decoding for word recognition, while skilled reading (or the reading of familiar words) relies on direct retrieval of word-specific orthographic representations, e.g. Refs. [21,22,73]. On the other hand, alphabetical decoding instructions are regarded as unnecessary by reading acquisition models assuming that beginning readers rely mainly on the retrieval of word-specific orthographic representations, while phonological decoding skills are implicitly acquired later, from the structure (e.g., the correlational relationship between orthographic patterns and sounds) of trained words, e.g. Refs. [57,82]. Explicit instruction on phonological decoding was even regarded as disadvantageous by the 'reading stages model' [32], suggesting that children receiving little instruction in letter-sound correspondences can be expected to skip the alphabetical reading stage, and proceed directly to the application of word-specific orthographic representations, presumably an advanced and more fluent stage of skilled reading.

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As alphabetical rules are rather complex and synthetic, it is not unreasonable to expect that explicit instruction on grapheme–phoneme correspondence is essential for learning. In studies of non-linguistic skill acquisition [18,24,50,60] but also for some linguistic skills [11], explicit instructions were found to improve learning, and sometimes to be essential for learning. Similarly, explicit instruction on phonological decoding was found to enhance reading acquisition ([2,4, 13,29,30,31,56,83], and see Ref. [73] for review). Moreover, mere exposure to alphabetical orthography was, in many cases, insufficient for inducing the discovery of the alphabetic principle in children [10,12,14,26,39,71].

On the other hand, there is evidence that complicated rules can be learnt implicitly [3,45,46,53,58,59]. It has even been claimed that implicit learning can be more efficient than explicit learning [3,50,60], since explicit learning requires extensive working memory resources, which may interfere with the process of proceduralization and automatization [60,76], thus reducing the benefits of training in terms of speed and accuracy [1,42]. Some studies of reading acquisition, in the classroom, suggest that grapheme–phoneme correspondences were learned by young beginning readers from training on whole words [27,78,79]. However, in natural settings, additional factors may have critically contributed to the children's acquired knowledge, e.g. knowledge of letter names, spelling exercises and explicit alphabetical instruction outside the classroom [78].

Implicit learning of orthographic regularities in beginning readers was reported by Pacton et al. [55], who showed that 1st grade children were sensitive to the legal position of doubled letters in French. The children generalized their knowledge to letters that are never doubled, suggesting that they acquired orthographic knowledge that was abstracted beyond its surface features. This generalization, however, was incomplete, suggesting that participants developed sensitivity to statistical features of the words, rather than acquired rule-based knowledge.

Rule-like behavior, as a result of implicit learning, is evident in Artificial Grammar Learning (AGL) studies. In AGL subjects are required to memorize letter strings, with no awareness of the underlying grammatical rules. When they are later required to judge the grammaticality of novel letter strings, their performance is often above chance level, even when the items are composed of different letters (preserving the grammar rules), although unable to explicitly describe the rules. This finding was taken as an indication for implicit learning of the abstract grammar rules [45,46,58,72]. However, recent studies have suggested that probabilistic learning of surface features, rather than rule abstraction processes, can account for the performance in these tasks [9,17,55,58,62].

The debate on the necessity of explicit rule instruction for the acquisition of rule-based knowledge is also relevant to studies concerned with attainment of ''automaticity'' in second language acquisition [23,63,70]. According to one view, second language acquisition is mainly implicit and independent of ''conscious'' (declarative) processes [48]. Opponents of this view have argued that the allocation of attention to the form (structural aspect) of the input is essential, although not sufficient, for SLA, and therefore the structural rules have to be explicit [68]. Explicit knowledge, however, may evolve either from explicit instructions or extracted from the input [52]. Robinson [63] explored the interaction between rule-based knowledge and 'memory-based' (specific exemplar) knowledge on the one hand, and implicit and explicit instructions on the other hand, when teaching English grammar rules to Japanese adults. Only the group that received explicit instruction on the rules acquired rule-based knowledge that was generalizable to new sentences, while implicit training resulted in memory-based knowledge, specific to the trained items, and limited in its generalizability.

In a recent study [5], we directly addressed the question of whether whole-word training results in the formation of word-specific orthographic representations, or rather in the formation of letter representations and phonological decoding skills in literate adults. Experienced adult readers received multi-session training on reading nonsense words written in an artificial Morse-like script, in which a sequence of two to three symbols represented a letter. Three training conditions were compared within each subject: alphabetical whole words with letter decoding instruction (Explicit), alphabetical whole words (Implicit), and non-alphabetical whole words, with no consistent correspondence of letters to sounds (Arbitrary). All training conditions resulted in very effective learning with no significant differences between training conditions. The pattern of results in the transfer tests, however, suggested that letter knowledge did not evolve spontaneously from training on whole words in the implicit condition. Moreover, we found that declarative knowledge of letters evolved only after experience with explicit instruction. The explicit training condition, on the other hand, did result in specific letter knowledge, but was found to be disadvantageous, relative to whole-word learning, with respect to the ability to transfer the effects of training to a new alphabetic system. Our results also showed that much of the performance gains in all training conditions were specific to the requirements (constraints) of a given task, but transferable across stimuli and training conditions.

In the current study, we show minimal conditions in which letter knowledge may evolve in some individuals from training on whole-word recognition. The training was modified to include a larger number of trained words and a simplification of the segmentation rules. We reasoned that doubling the number of trained words while preserving the number of letters and the total number of task repetitions may enhance letter learning in two ways. (1) The number of word repetitions following this manipulation is decreased relative to letter repetitions, thus hampering orthographic pattern recognition. (2) Each letter is presented in the context of different words, thus increasing its saliency. A number of studies have shown that increasing the variability of trained stimuli can enhance the transfer of the acquired knowledge to novel task variations [1,34,35,54,64,74,75]. In addition to increasing the number of trained words, the segmentation rules were simplified to facilitate segmentation, by using a fixed number of symbols per letter and shorter symbol strings.

By introducing the above modifications to the paradigm, we here show that letter decoding can evolve from implicit training on whole-word recognition. However, the implicitly derived letter knowledge was found to be disadvantageous compared to explicit letter knowledge in terms of its long-term retention and the transfer to new words. Furthermore, we found that the implicitly derived letter knowledge manifested in task performance was independent from letter knowledge as measured in a declarative recognition test.

## 2. Materials and methods

### 2.1. Subjects

A total of 24 adult volunteers, ages between 17 and 29, with normal linguistic and reading skills participated in the experiment and were paid for their time. The group consisted of 9 males and 15 females. Each subject participated in two training conditions: an alphabetical condition and an arbitrary condition, serially.

### 2.2. Stimuli

The training stimuli consisted of two sets of 12 nonsense words written in an artificial Morse-like script. Each word was composed of two consonants (C) and one vowel (V), and each training set contained all phonological patterns: CVC, VCC and CCV, with the difficulty of pronunciation equalized across sets. Four consonants and two vowels were used to compose all non-words in a given set, with each element repeating six times. E.g.:

> Set 1: LOP, PNO, APL, TOL, TPO, NAL, NLO, LAT, ONT, PNA, APT, TNA.
> Set 2: RUB, BMU, MUR, BRI, UMK, MIR, BKU, KRU, IRK, KMI, IMB, BKI.

One methodological problem with studying reading acquisition in adult subjects is that their extensive reading experience with alphabetical systems may predispose them to apply their word segmentation skills to the novel orthography. We attempted to minimize this effect by using a Morse-like script, modified from Bitan and Karni [5], in which a sequence of two symbols represented one letter and four symbols in different orders were used to compose all letters. The learning of the alphabetic code for this artificial script would, therefore, entail the segmentation of the symbol string into letters as well as the mapping of letters to sounds. Each symbol appeared in three out of the six letters. In each set of six letters, two pairs were mirror images of each other (the same symbols in a reversed order), and two letters (one consonant and one vowel) were unique combinations of symbols. (e.g.: P:*< L:<* T: □╡ A:╡□ N:*╡ O:<□). The other six sequences of the same symbols were used to represent another set of graphemes used in the 'letter-transfer' condition, explained below (e.g.: D:╡* F: □< S: □* Y:╡< E: □< U:<╡).

Each non-word was represented in the novel script using two different transformations: an alphabetical transformation, in which each phoneme consistently corresponded to a letter (e.g.: PNO: *<*╡<□; LOP: <*<□*<), and an arbitrary transformation, in which phoneme to letter correspondence differed across words (e.g.: PNO: □╪□*<; LOP: *≪**╡). Thus, the symbol strings in the arbitrary condition could only be read as pictographs (in similarity to Japanese Kanji).

### 2.3. Apparatus

The stimuli were presented on a 17-in. 60-Hz PC screen, with each item subtending 1° viewing angle, from a viewing distance of 60 cm. Stimulus presentation as well as the recording of responses (using a standard three button mouse) was controlled by 'Psy', a psychophysical measurements program, operating on Linux environment (Y. Bonneh, 1998).

### 2.4. Experimental procedure

Each subject was trained in two training conditions successively: an alphabetical condition—training on alphabetical non-words, and an arbitrary condition—training on non-alphabetical non-words with no consistent mapping of graphemes to phonemes (pictographs). In the alphabetical condition half of the subjects were trained in the 'explicit' condition-given instruction on the grapheme–phoneme correspondence prior to training, and half of the subjects were trained in the 'implicit' condition—with no instruction of grapheme–phoneme correspondence. In each group half of the subjects were trained on the arbitrary condition before the alphabetical condition, and half of the subjects were trained on the alphabetical condition before the arbitrary condition. The two sets of trained non-words were written using a different set of symbols each, and were balanced across training conditions.

The first session of each training condition started with a 'whole-word instruction' block, in which the subject was presented with each target non-word in novel script with its corresponding translation to Latin letters below (Fig. 1). Each stimulus was presented for 2000 ms. and subjects were instructed to read it aloud and memorize the association. The non-words appeared in a fixed order that repeated for three times (total of 36 trials). A 'letter-instruction' block was given prior to the 'whole-word instruction' block only in the explicit training condition. The 'letter-instruction' block consisted of 30 trials in which the individual letter patterns

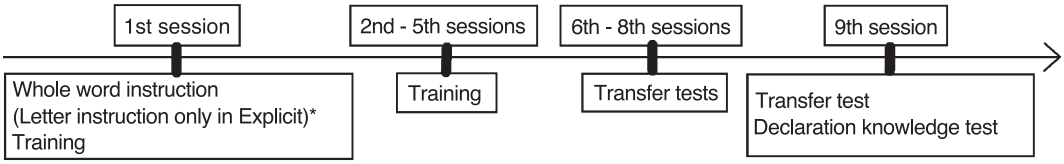

Fig. 1. Overall study design. (*) Letter instruction was given only in the 1st session of the explicit training condition.

in the new script were presented together with their corresponding Latin letter translation, each pair for 2000 ms. Subjects were required to pronounce the related phoneme and memorize the association. The letters appeared in a fixed order that repeated for five times (total of 30 trials).

After the instruction block(s), six training blocks were administered. In each trial a target word appeared for 800 ms with a translation to Latin letters presented below. The subject's task was to indicate, for each test item, whether the translation to Latin was correct or not, by pressing one of two keys (two alternative forced choice). Auditory feedback was given for errors. Each block consisted of 48 trials. In each training condition subjects were given training on five daily sessions, spaced 1–3 days apart. In sessions 2–5, only the training blocks were administered, and the training procedure was identical in all conditions.

At the end of the five training sessions in each training condition the transfer of learning gains to novel stimuli was tested, in order to probe the level of neural representations at which learning occurred [43] (Fig. 1). Four transfer tests were administered, 12 non-words in each test. The 'word-transfer' test consisted of new non-words composed of the original letters, and written with the same set of symbols. (E.g. after training on: PNO: *<*╡<□ testing the transfer to: NOP: *╡<□*<). The 'letter-transfer' test consisted of new non-words composed of new letters written with the same set of symbols (e.g. after training on PNO: *<*╡<□ testing the transfer to: DUF: ╡*<╡□<). A comparison of 'word transfer' to 'letter-transfer' was planned to provide an indication as to whether learning occurred at the level of letters and the alphabetical correspondence rules or at the level of whole words. A third transfer test was the 'symbol-transfer' test in which the original non-words were written using a new set of symbols, with consistent mapping between the sets of symbols. Thus, the pattern of symbol repetitions and internal symmetries within each string was preserved (e.g. after training on PNO: *<*╡<□ testing the transfer to PNO: -╥-^╥. The fourth transfer test was the 'grapheme-transfer' test, in which the original non-words were written using a still new set of symbols, in a completely new sequence. The 'grapheme-transfer' test was included to assess the effect of preserving the trained word. Thus, a difference between 'symbol-transfer' and 'grapheme-transfer' would arise if learning occurred at the level of the structure of the sequence, independent of the specific symbols.

Each of the four transfer tests was administered in a separate session with the order of transfer tests fixed for all subjects ('word-transfer'; 'symbol-transfer'; 'letter-transfer'; 'grapheme-transfer'). In each of the four transfer sessions, subjects first performed three blocks of the task using the originally trained non-words. The level of performance of the task with the trained stimuli served as the reference for calculating the transfer of performance gains to the transfer stimuli. Subjects then performed a 'whole-word instruction' block in which the transfer stimuli and their Latin letter equivalents were presented. No 'letter instruction' was given during the transfer sessions. Finally, subjects performed six blocks of the task using the transfer stimuli. A transfer ratio was calculated for each subject in each transfer condition in the following manner. The difference between the mean performance in the transfer blocks and mean performance in the first training session was divided by the difference between the last performance of the original stimuli (in the transfer session) and performance in the first training session.

$$\text{Transfer ratio} = \frac{(\text{Transfer} - \text{Trained 1st session})}{(\text{Trained last session} - \text{Trained 1st session})}$$

*Declarative knowledge test* (in a pen and paper format) was administered at the last (9th) session of each training condition. Subjects were required to write the appropriate translation of symbol strings to Latin letters. The symbol strings included in the test were: (a) the 12 trained non-words; (b) the six component letters of the trained non-words; (c) 12 novel non-words composed of the original letters.

*Delayed performance* in the trained task was tested after a period of 8–13 months (mean 10 months). 10 Ss from the explicit group and 5 Ss from the implicit group were recruited for two additional sessions. In each session they performed one of the training conditions, in the same order they were performed during training. In each training condition the word-instruction block was administered first, followed by six blocks of training. The letter-instruction block was not administered at the delayed phase.

All data was analyzed using the General Linear Model (GLM).

## 3. Results

The explicit and arbitrary training conditions resulted in different outcomes, both in terms of the time-course of learning and in terms of the transfer of learning gains to different stimuli. Altogether, the results show that the outcome of the implicit training condition had the characteristics of both: explicit and arbitrary training.

### *3.1. Learning curves*

All training conditions induced significant improvement in the translation task throughout training, both in terms of accuracy and in terms of reaction time (RT), with no speed–accuracy trade-off. The GLM analyses with group and condition order as between-subject variables, and training condition, session, and block as within subject variables, showed significant effects of session ($F(4,80) = 213.2$, $p < 0.001$; $F(4,80) = 67.1$, $p < 0.001$ for accuracy and RT, respectively) and of block ($F(5,100) = 42.8$, $p < 0.001$; $F(5,100) = 40.3$, $p < 0.001$ for accuracy and RT, respectively). Learning curves in all conditions had a good fit to power functions ($R^2 = 0.94–0.97$). However, the time-course of learning was different in the different training conditions.

Fig. 2a shows that the performance in the explicit condition was more accurate compared to the performance in the arbitrary condition throughout the entire training process. A GLM analysis on the accuracy within the explicit group revealed a significant difference between the explicit and arbitrary conditions ($F(1,10) = 18.8$, $p < 0.01$). However, performance in the explicit condition was also significantly slower than performance in the arbitrary condition ($F(1,10) = 33.6$, $p < 0.001$) (Fig. 2c). There was no effect of the order of conditions neither on the accuracy of performance, nor on the RT (the interaction between order and condition was not significant, for both accuracy ($F(1,10) < 1$) and RT ($F(1,10) = 1.3$)). Thus there was no transfer of learning gains between the initial and the subsequent training condition in the explicit training group.

Training in the implicit condition showed similarities to both the explicit and the arbitrary conditions. In similarity to the explicit condition, accuracy of performance in the implicit condition was significantly higher than in the arbitrary condition ($F(1,10) = 7.85$, $p < 0.05$) (Fig. 2b). Between-group analyses revealed significant difference in the accuracy between the explicit and implicit conditions only in the two initial sessions ($F(1,20) = 5.0$, $p < 0.05$). However, analysis of RTs showed significantly faster responses in the implicit compared to the explicit condition throughout training ($F(1,20) = 17.9$, $p < 0.001$). RT in the implicit condition was similar to that in the corresponding arbitrary condition ($F(1,10) = 1.6$, $p = 0.2$) (Fig. 2d). Moreover, in the implicit group there was a significant effect of condition order on both accuracy ($F(1,10) = 13.5$, $p < 0.01$) and RT ($F(1,10) = 26.7$, $p < 0.001$). There was clear advantage in performance (both accuracy and speed) of the second training condition in the sequence, with implicit training first contributing to the arbitrary condition (second) and vice versa. Thus, unlike the explicit condition there was significant transfer between the implicit and the arbitrary training conditions.

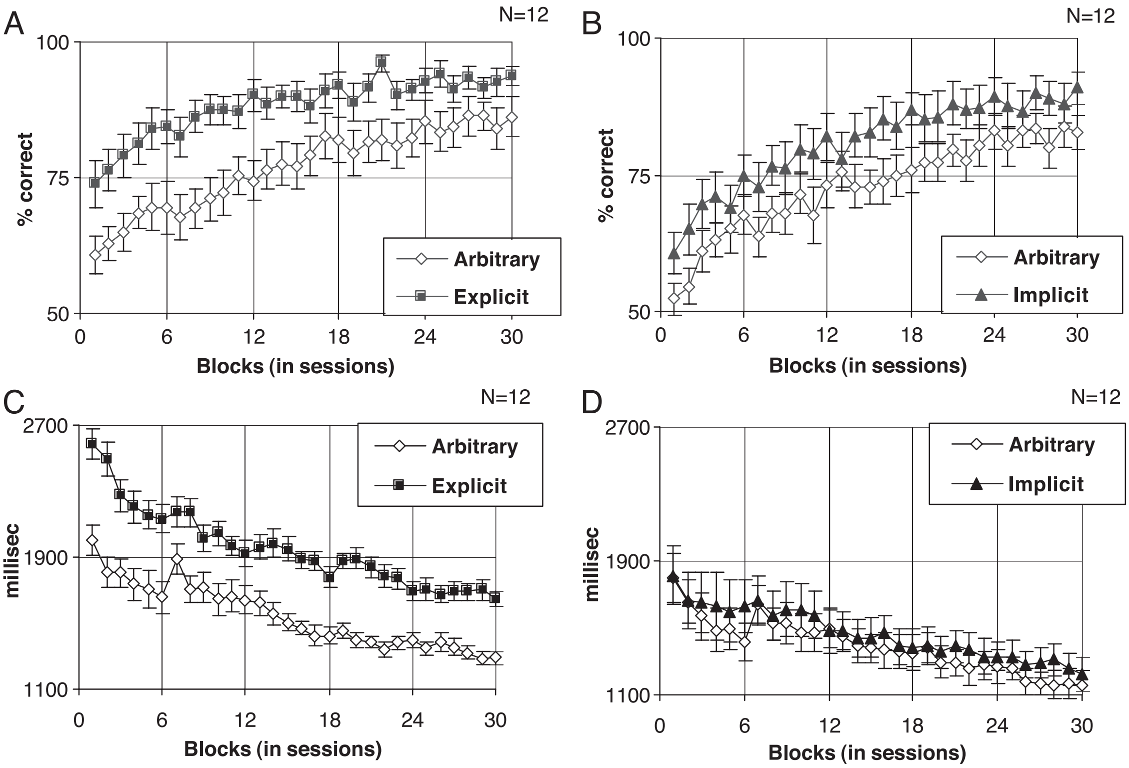

Fig. 2. Learning curves for the explicit group (A, C) and the implicit group (B, D). Accuracy (A, B) and reaction times (C, D) are shown for the alphabetic and the arbitrary conditions. Vertical lines indicate final blocks of each training session.

Performance at the beginning of session 2 was found to be much slower (as well as less accurate) compared to the performance attained at the end of session 1. This was significantly more pronounced for the arbitrary conditions in both training groups (Fig. 3). In a GLM analysis on the differences in RT between sessions (first block minus last block of previous session) across groups, the interaction of session and training condition was significant ($F(4,88)=5.6$, $p<0.001$). In paired *t*-tests on the RT change from the 1st to the 2nd session, a significant difference was found between the explicit and arbitrary conditions ($t(11)=2.3$, $p<0.05$) and between the implicit and arbitrary conditions ($t(11)=2.6$, $p<0.05$).

### 3.2. Transfer results

The results of the transfer tests indicate that the ability to transfer the acquired knowledge to untrained stimuli was markedly different following training in the explicit and arbitrary conditions (Fig. 4a). The most striking finding was that the pattern of transfer results in the implicit condition has characteristics of both the explicit and the arbitrary conditions (Fig. 4b). (All the transfer ratios discussed below relate to the measure of accuracy).

Performance in the 'word-transfer' test in the explicit condition was significantly higher than performance in the 'letter-transfer' test. Transfer ratios in the word transfer and in the 'letter-transfer' tests were 0.69 and 0.21, respectively ($t(9)=3.49$ $p<0.01$) (Fig. 4a). The advantage of words composed of the original letters compared to words composed of new letters suggests that the letters were learnt in the explicit conditions. However, the advantage of the trained words compared to the 'word-transfer' ('word-transfer' ratio < 1) suggests that participants in the explicit condition have acquired some word-specific knowledge in addition to the letter knowledge. As expected there was no advantage of 'word-transfer' over 'letter-transfer' in the arbitrary condition. A combined analysis of the arbitrary condition in the two groups of subjects showed no significant difference between the word and 'letter-transfer' ratios ($t(22)=1.64$, $p=0.1$) (Fig. 4a and b). Moreover, in the explicit group, performance in the 'word-transfer' test was significantly higher in the explicit condition than in the corresponding arbitrary condition (transfer ratios were 0.69 and 0.23, respectively, $t(10)=3.17$, $p<0.05$) (Fig. 4a).

The highest degree of transfer in the arbitrary condition in the two groups of subjects was evident in the 'symbol-transfer' test, with 'symbol-transfer' significantly higher than 'grapheme-transfer' (Fig. 4a and b). Transfer ratios of the 'symbol-transfer' and 'grapheme-transfer' tests, in a combined analysis of the arbitrary condition in the two groups, were 0.48 and 0.29, respectively ($t(17)=2.78$ $p<0.01$). This advantage of 'symbol-transfer' over 'grapheme-transfer' suggests that local patterns of elements (such

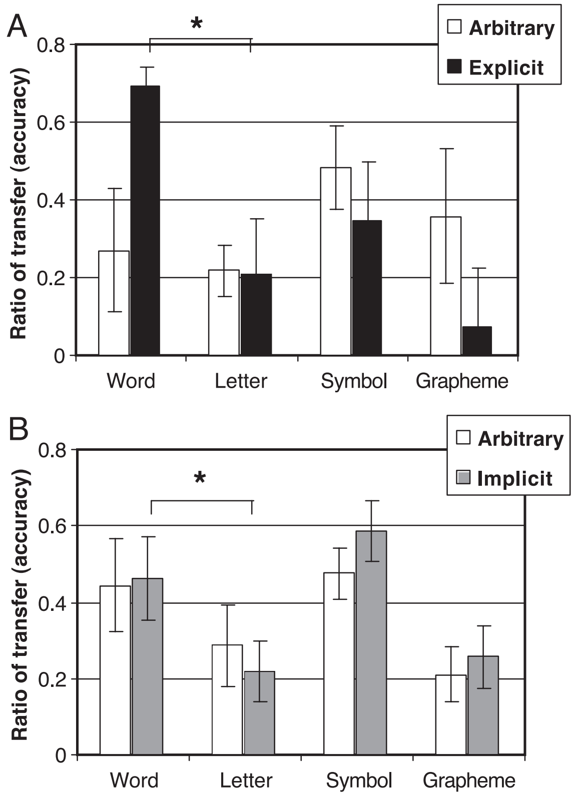

Fig. 4. Transfer results in the Explicit (A) and Implicit (B) groups. The measure for transfer was calculated as: (mean performance in the transfer session − first training session)/(last training session − first training session), with transfer ratio of 1.0 indicating full transfer. (*) Significant 'word-transfer' 'letter-transfer' difference.

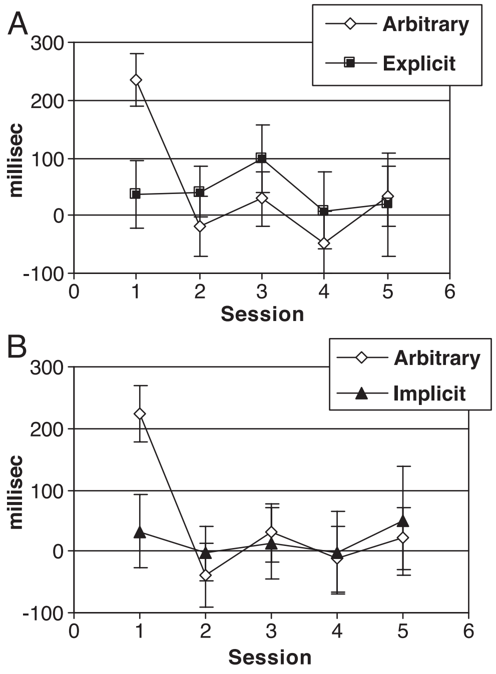

Fig. 3. The difference in reaction times between the final block of the session and the first block of the following session is shown in the Explicit (A) and Implicit (B) groups. Positive values indicate increase in reaction time (i.e. slower performance).

as symmetries and repetitions), independent of the specific symbols, were learnt in the arbitrary condition. However, an advantage of the 'symbol-transfer' over the 'grapheme-transfer' test was also found in the explicit training condition (transfer ratios were 0.34 and 0.08, respectively, $t(11) = 3.69$, $p < 0.01$) (Fig. 4a).

In similarity to the explicit condition, Fig. 4b shows that following training in the implicit condition, performance in the 'word-transfer' test was significantly higher than performance in the 'letter-transfer' test (transfer ratios were $0.46 > 0.22$, respectively, $t(11) = 2.41$, $p < 0.05$). Thus, although participants in the implicit condition had no instruction on the letters, the transfer tests results suggest that they have acquired knowledge of the alphabetic structure of the words. However, in similarity to the arbitrary condition, the highest degree of transfer in the implicit condition was found in the 'symbol-transfer' test (transfer ratio was 0.59). A significant advantage of 'symbol-transfer' over 'grapheme-transfer' was also evident in the implicit training condition (transfer ratios were 0.59 and 0.26, respectively, $t(11) = 3.493$, $p < 0.01$). Thus all training conditions were found to result in higher 'symbol-transfer' compared to 'grapheme-transfer'.

### *3.3. Subgroups in the implicit condition*

To investigate the relationship between performance during training and the acquisition of alphabetic structure cues (will be further denoted as 'letter knowledge'), the implicit group was split into two subgroups of high- and low-letter-knowledge in the implicit condition. The difference between 'word-transfer' and 'letter-transfer' ratios was used as the criterion. Thus, individuals with above-average difference between 'word-transfer' and 'letter-transfer' were assigned to the high-letter-knowledge subgroup, and individuals with below-average difference were assigned to the low-letter-knowledge subgroup (Fig. 7, *x*-axis). Each subgroup consisted of 6 Ss, and the order of conditions was found to be balanced across the subgroups, enabling direct comparisons of learning curves. The subgroups were not different in terms of accuracy: in both subgroups accuracy was higher in the implicit condition compared to the arbitrary condition, and there was no interaction between subgroup and condition ($F(1,9) < 1$) (Fig. 5a and b). However, there was a significant interaction between subgroup and condition for the RT measurement ($F(1,9) = 5.5$, $p < 0.05$). In the high-letter-knowledge subgroup RTs in the implicit condition were slower than in the arbitrary condition (non-significant trend $F(1,4) = 6.72$, $p = 0.06$), while in the low-letter-knowledge subgroup RTs in the implicit condition were as fast as in the arbitrary condition ($F(1,4) < 1$) (Fig. 5c and d). Thus, participants who acquired letter knowledge tended to perform the word-recognition task at a slower speed than those who did not acquire letter knowledge.

The difference between the subgroups with high- and low-letter-knowledge in the implicit condition, and the finding of a high degree of 'symbol-transfer' in the implicit condition suggests the possibility that different individuals acquired either alphabetical or word-specific knowledge. Thus, if individuals with high letter knowledge would have less knowledge of the local patterns, a negative correlation would be expected between the

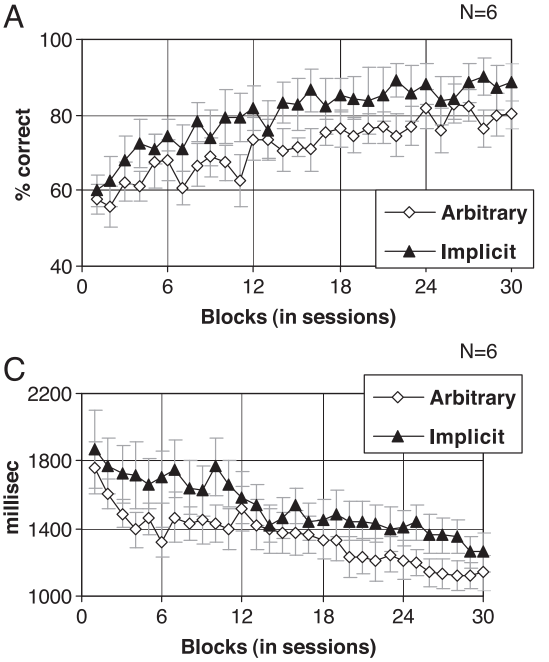

Fig. 5. Learning curves for participants with high-letter-knowledge (A, C) and participants with low-letter-knowledge (B, D) in the Implicit group. Accuracy (A, B) and reaction times (C, D) are shown as in Fig. 2.

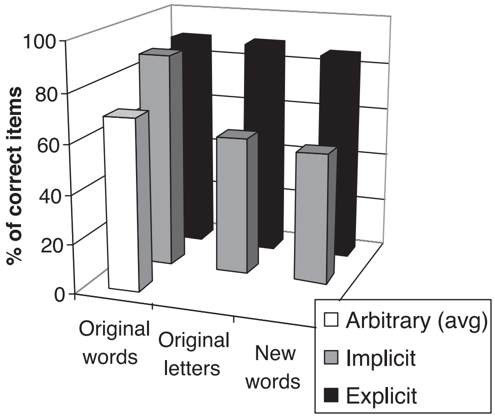

Fig. 6. The declarative knowledge test in the three training conditions (Arbitrary condition averaged across the two groups). In the arbitrary condition, the 'Original letters' and 'New words' translation could not be tested.

'symbol-transfer' ratio and the difference between 'word-transfer' and 'letter-transfer' ratios. No (negative) correlation was found between the 'symbol-transfer' ratio and the difference between 'word-transfer' and 'letter-transfer' ratios in the implicit condition ($r = 0.17$). Thus, this analysis supports the notion that, in similarity to the explicit condition, participants in the implicit condition gain both letter knowledge and word-specific knowledge simultaneously.

### 3.4. The declarative data

Memory for trained words, as measured in the declarative test, was significantly higher for the alphabetical compared to the arbitrary conditions, with no difference between the implicit and explicit training conditions (mean accuracy in the explicit and implicit conditions was 0.89, compared to 0.70 in the arbitrary condition, $t(23) = 3.28$, $p < 0.01$) (Fig. 6). Declarative knowledge of letters, measured by recognition of the original letters and by decoding new words, was highest in the explicit condition (0.89 and 0.86, respectively). However, declarative letter knowledge was also evident in the implicit condition (0.57 for recognition of the original letters and 0.54 for decoding new words, significantly higher than zero, $t(11) = 5.3$, $t(11) = 4.2$ $p < 0.001$). Nevertheless, declarative letter knowledge in the implicit condition was significantly lower than that achieved in the explicit condition (recognition of original letters and decoding new words $t(22) = 2.32$, $p < 0.05$; $t(22) = 2.21$, $p < 0.05$, respectively) (Fig. 6). Notably, there was no correlation between the declarative letter knowledge in the implicit condition (as measured by both recognition of original letters and decoding of new words) and the letter knowledge measured by the difference between 'word-transfer' and 'letter-transfer' ($r = (-0.06)$ for both original letter recognition and for decoding of new words) (Fig. 7).

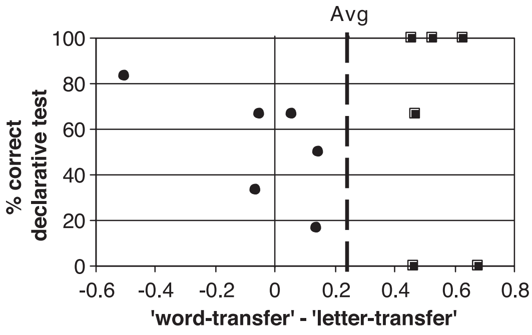

Fig. 7. The relationship between declarative letter knowledge (Original letters test), and the 'word-transfer' 'letter-transfer' difference between, in the implicit group. Dashed vertical line indicates the average 'word-transfer' 'letter-transfer' difference. Participants above the group mean (squares) were subgrouped as having high-letter-knowledge, and participants below the group mean (circles) were subgrouped as having low-letter-knowledge.

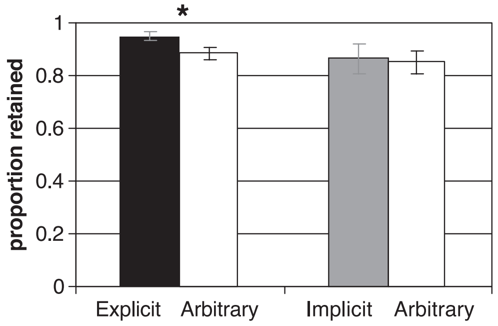

Fig. 8. Learning gains retained at 10 months post training. The mean accuracy in the delayed session normalized to the performance in the last (9th) session, is shown for the Explicit (left pair of bars) and Implicit (right pair of bars) groups.

### 3.5. Long-term retention

Learning gains were highly preserved 8–13 months (10 months on average) post training in all training conditions. Mean accuracy in the delayed (retention) session, normalized to the accuracy of performance of the trained stimuli in the final (9th) session, was above 85% in all training conditions (Fig. 8). However, in the explicit group, accuracy was significantly higher in the explicit condition compared to the corresponding arbitrary condition (0.95>0.88, respectively, $t(9) = (-2.97)$, $p < 0.05$). In the implicit group, there was no significant difference between the performance in the implicit and the corresponding arbitrary condition in the delayed session (0.86 and 0.85, respectively, $t(4) = (-0.26)$).

## 4. Discussion

Our results show that participants in all training conditions improved their performance significantly, both in terms of accuracy and reaction times, and that learning gains were highly preserved after a long delay (10 months) irrespective of the training condition. However, distinct differences were found between the results of training in the explicit and arbitrary conditions, while learning in the implicit condition had some strong similarities both to the explicit and to the arbitrary conditions. Performance in the explicit condition was slower but more accurate than performance in the arbitrary condition. Moreover, the results of the transfer tests showed that while explicit training resulted in both effective letter knowledge as well as word-specific recognition skills, training in the arbitrary condition resulted only in word-specific knowledge. In the implicit condition, a subgroup of the participants has learned to recognize the letters that composed the trained words (having received no direct instruction on the letters). This letter knowledge was manifested in the ability to read new words composed of the original letters in the transfer tests. However, this effective letter knowledge was not correlated with the performance in a declarative letter recognition test, indicating that the letter knowledge in this subgroup evolved implicitly, independent of declarative letter knowledge.

Altogether our findings suggest that letter-decoding skills may evolve, under specific conditions, from implicit training in whole-word recognition. Nevertheless, our results suggest that the implicitly derived letter knowledge is not more fluent, and may even be disadvantageous, compared to the explicitly instructed letter knowledge, in terms of its long-term retention and the transfer to new words composed of the original letters. Finally, in both the explicit and the implicit conditions, letter knowledge and word-specific patterns knowledge evolved in parallel, contributing to performance in different proportions. Even given very simple segmentation rules, explicit instructions on letters, and adult participants, experienced in reading alphabetic scripts, word-specific recognition contributed significantly to performance.

### *4.1. Distinct processes in the explicit and arbitrary training conditions*

There are several indications that the outcome of training in the explicit and in the arbitrary conditions were different. (1) Performance in the explicit condition was more accurate than performance in the arbitrary condition throughout the entire training process (Fig. 2a). (2) Performance in the explicit condition was slower than performance in the arbitrary condition, with the difference between conditions maintained throughout training (Fig. 2c). (3) There was no effect of order between the explicit and arbitrary conditions (i.e. prior training in the arbitrary condition did not improve performance in the subsequent explicit condition, and vice versa), indicating that there was no transfer of learning gains between the two conditions. (4) The explicit condition showed a higher proportion of preserved knowledge in the long-term retention test (Fig. 8). (5) The differential pattern of transfer results suggests that different levels of neural representations were involved in learning in the explicit and arbitrary training conditions (Fig. 4a).

In the explicit condition, the large and significant advantage for the 'word-transfer' test (new words composed of the original letters) over the 'letter-transfer' test (new words composed of new letters) suggests that participants learned to recognize the letters. However, performance in the 'word-transfer' test was lower than performance in the trained words (incomplete transfer), suggesting that word-specific knowledge was acquired in the explicit condition in addition to letter knowledge. In the arbitrary condition, the 'word-transfer' ratio was significantly lower than in the explicit condition, and was not advantageous compared to the 'letter-transfer' ratio. The highest transfer ratio after training in the arbitrary condition was evident in the 'symbol-transfer' test (trained words written using new symbols, preserving the structure of the trained sequence of symbols, e.g. from PNO: *<*╡< □ to PNO: -╥-^╥ (·). The high degree of 'symbol-transfer' together with the significant advantage for 'symbol-transfer' over 'grapheme-transfer' (trained words written using new symbols in a completely new sequence) suggests that participants in the arbitrary condition learned to recognize the structure of the sequence using local patterns of symbol repetitions and symmetries [5].

In a recent fMRI study, wherein identical stimuli and training conditions were used [6], distinct patterns of brain activation were found following training in the explicit and arbitrary conditions, supporting the conclusion that the training conditions tested in the current study indeed resulted in different types of knowledge. Distinct patterns of brain activation were also found in neuroimaging studies that compared alphabetical and non-alphabetical reading in natural scripts [15,33,49,66,67]. In a PET study, Law et al [49] found that the Kana (alphabetical) Japanese script was associated with greater activity in the left supramarginal and angular gyri, which is considered to be involved in grapheme–phoneme mapping [7,28,33,49,65]. The non-alphabetical Japanese Kanji script was associated with greater activation in the visual association areas [49]. However, others [47] have reported similar activation patterns induced by both Kana and Kanji, mainly in the posterior inferior temporal areas.

Our data shows a significant advantage for the 'symbol-transfer' test over the 'grapheme-transfer' test even in the explicit condition. Together with the incomplete 'word-transfer', this finding suggests that participants in the explicit condition have acquired word-specific pattern recognition in addition to letter decoding knowledge. This conclusion is supported by recent fMRI results showing that the reading of well-trained words in the explicit condition did not require letter decoding [6]. This finding is in accord with the finding of Robinson [63] that showed that explicit instruction on grammar rules in second language learning resulted in both 'rule-based' knowledge that was transferable to new sentences, as well as 'memory-based' knowledge that was specific to the trained sentences, and manifested in an advantage for the trained sentences compared to the new sentences. An alternative interpretation for the advantage of the 'symbol-transfer' over the 'grapheme-transfer' is that the acquired letter knowledge in the explicit condition involved knowledge of the relationship between letters (e.g. 'P is the reversed order of L' when P: *< and L: < *), which were preserved in the 'symbol-transfer'.

The transfer tests implicate letter decoding as an important factor in the performance gains in the explicit condition. A possible interpretation for the higher accuracy of performance during training in the explicit condition is that fewer and shorter units were learnt in the explicit compared to the arbitrary condition. (There were 6 letter-units of 2 symbols each, in the explicit condition, compared to 12 word-units of 6 symbols each, in the arbitrary condition.) The slower RTs in the explicit condition may have, therefore, resulted from a process of decoding (including segmentation) which presumably is slower than a direct retrieval of word-specific representations, as suggested by the delayed phonology hypothesis [19,20].

The higher proportion of preserved performance gains after a long delay indicates that the learning in the explicit training was more resistant to forgetting compared to the learning in the arbitrary condition. The gains in the arbitrary condition were less preserved compared to the alphabetical conditions, in terms of RT, even during the interval between the first and the second training session (Fig. 4a). As each letter appeared six times in a single set of (12) different words, participants in the explicit condition have received six times as many repetitions on each letter-unit compared to the number of repetitions of each word-unit in the arbitrary condition. The more intensive training per unit in the explicit condition may account for the higher preservation of the acquired knowledge. One possible interpretation is that the more intensive training in the explicit condition resulted in a more proceduralized routine of letter decoding (i.e. involved a larger contribution from procedural learning mechanisms). Learning in the arbitrary condition, on the other hand, was less resistant to forgetting because of a greater contribution from declarative memory. This interpretation is in accord with the notion that procedural learning requires numerous repetitions, but is more resistant to forgetting compared to declarative memory [9,16,43]. Alternatively, the higher proportion of preserved learning gains in the explicit condition may have resulted from the higher accuracy achieved at the end of training. However, the latter interpretation is not supported by the lower retention of learning gains found in the implicit condition, in which performance at the end of training was as high as in the explicit condition.

### 4.2. Implicit learning of letters

Performance in the implicit condition was similar to performance in the explicit condition in two aspects. First, accuracy during training in both the implicit and explicit conditions was higher than in the arbitrary condition (Fig. 2b). Second, a significant advantage for the 'word-transfer' over the 'letter-transfer' test was found in the implicit condition (Fig. 4b), suggesting that participants have learned to segment the words and recognize the individual letters even without any direct letter instruction. However, performance in the implicit condition was also similar to performance in the arbitrary condition. First, reaction times during training were similar in the implicit and arbitrary conditions, and both were faster than in the explicit condition (Fig. 2d). Second, there was a significant effect of order between the implicit and the arbitrary conditions, both in terms of accuracy and RT, suggesting that a common level of representation was involved in both training conditions. Third, the proportion of the acquired knowledge retained after a long delay was similar in the implicit and arbitrary conditions, and lower than in the explicit condition (Fig. 8). Finally, the results of the transfer tests showed that the highest transfer ratio was found in the 'symbol-transfer' test (Fig. 4b). Together with the advantage of the 'symbol-transfer' over the 'grapheme-transfer' test, this finding suggests that participants have learned to recognize structural aspects such as internal-pattern repetitions and symmetries within the whole-word patterns. The similarity of the implicit condition to both the explicit and arbitrary conditions was also evident in terms of the pattern of brain activation in our recent fMRI study [6].

Individuals with high implicit letter knowledge, in similarity to the explicit condition, were slower in the implicit condition compared to the arbitrary condition, while individuals with low implicit letter knowledge were as fast in the implicit as in the arbitrary condition. Thus, the results indicate that in similarity to the explicit condition, participants in the implicit group may have evolved two different procedures: letter decoding and word-specific pattern recognition skills. The individual differences within this group may, therefore, be explained by the individual differences in the relative contribution of each procedure. Those participants who relied mainly on letter decoding were slower, while those depending mainly on word-specific pattern recognition were faster. However, even participants in the 'low-letter-knowledge' subgroup were more accurate during training in the implicit compared to the arbitrary condition, suggesting that they may have acquired partial knowledge of the letters.[1] Moreover, our results show that letter knowledge in the implicit condition was not negatively correlated with the 'symbol-transfer' ratio. Together with the evidence for word-specific knowledge in the explicit condition, these results suggest that letter decoding and word-specific recognition were not competing processes, but rather that both procedures may evolve simultaneously in implicit as well as explicit training.

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[1] One can consider, for example, the possibility that knowledge of the first single symbol in words that begin with a certain phoneme, without knowing how to segment the rest of the word, would increase accuracy during training. However, this knowledge may be insufficient to improve performance in the 'word-transfer' test because of a different distribution of first letters in the 'word-transfer' set of words.

Our results show that there was no correlation between the letter knowledge manifested in the transfer tests, and the declarative knowledge of letters (measured in the declarative test) after training in the implicit condition. A subgroup of the participants in the implicit condition acquired effective letter knowledge with no awareness of the letters, suggesting that letter knowledge in these individuals did not evolve from intentional extraction of the letters from the trained words in initial stages of training. Other participants showed declarative letter knowledge at the end of training, with no indication of letter decoding during task performance. This finding may indicate that the declarative letter knowledge did not evolve from the implicitly derived (procedural) letter knowledge, but rather was realized later, during the declarative knowledge test. The independence of procedural and declarative letter knowledge suggests that letter knowledge may be represented in the adult brain by both procedural and declarative mechanisms. This finding is in accord with studies showing independent implicit learning in the AGL paradigm, even in amnesic patients [45,46,59,72], and with studies showing differential patterns of brain activation after explicit and implicit training [38,61]. Our results are in accord with the finding of Kirkhart [44] who showed that even when declarative knowledge evolved in an AGL task, it was neither required nor predictive of procedural knowledge.

The finding that letter knowledge can be acquired implicitly is in accord with the results of Pacton et al. [55], which showed implicit learning of orthographic regularities in beginning readers. Pacton et al. found that 1st grade children were sensitive to the legal position of doubled letters in French, and generalized their knowledge to letters that are never doubled, suggesting that they acquired orthographic knowledge that was abstracted beyond its surface features. This generalization, however, was incomplete, suggesting that participants developed sensitivity to statistical features of the words, rather than acquired rule-based knowledge. Recent neuroimaging results lend support to the notion that the practice-related performance gains accrued in the artificial grammar paradigm may be mediated by the relative familiarity of sub-strings and fragments of the letter string, rather than by the learning of the underlying abstract rules [77]. Although the current study was not designed to provide evidence for either the rule-based knowledge or statistical learning hypotheses, our results can be accounted for by a statistical learning mechanism, resulting in a rule-like behavior. The letter knowledge acquired in the implicit condition may be accounted for by enhanced sensitivity to regular patterns in the input (i.e. a specific pair of symbols is associated with a specific letter), rather than indicating abstract rule learning. Furthermore, the high degree of 'symbol-transfer' in the current study is in accord with the finding of Pacton et al. [55], in showing that participants learned to recognize a pattern of repetitions and transferred their acquired knowledge to strings of untrained letters that preserved this pattern of repetitions. Moreover, the high 'symbol-transfer' ratio found in the arbitrary condition (in which there were no regularities across words) suggests that the transfer to new letters may occur even in word-specific knowledge, and supports Pacton et al.'s claim that it is not indicative of rule-based knowledge.

### *4.3. Letter segmentation depends on its effectiveness for task performance*

In a previous study [5], a more complex segmentation rule (two to three symbols per letter) and fewer words in a trained set (6 vs. 12) were used, with an otherwise identical paradigm. In similarity to the current results, an advantage of the 'word-transfer' over the 'letter-transfer' test was found in the explicit condition, and a high 'symbol-transfer' ratio was found in the arbitrary and implicit conditions. However, both alphabetical conditions of the previous experiment resulted in little effective letter knowledge. In the implicit condition, participants did not learn to recognize the letters from training on whole words (as indicated by the pattern of transfer results), and no declarative knowledge of the letters was found (unless subjects were given prior experience in the explicit condition) [5]. In the explicit condition, accuracy of performance during training was similar to that in the arbitrary condition. Moreover, there was a clear transfer of learning gains even between the explicit and arbitrary conditions, indicating shared processes across these conditions. Finally, the 'word-transfer' ratio in the explicit condition was higher than in the arbitrary condition only for the first transfer block, indicating only a transient advantage of letter knowledge in encountering new words. Indeed, the 'word-transfer' ratio in the explicit condition (for the entire transfer session) was much lower than in the current study (0.4 vs. 0.7).

In the current study, performance in both alphabetical conditions was found to rely more heavily on letter knowledge. This increased letter knowledge may be accounted for by the simplified word to letters segmentation, the enlarged trained stimuli set, or both. The enlarged training set may have contributed to letter learning by changing the effective unit of repetition from whole words to letters. Although the total number of letter repetitions was similar in both studies, the number of word repetitions decreased in the current study, resulting in an increased ratio of letter repetitions to word repetitions (from 3:1 in the previous study to 6:1 in the current study). The enlarged training set may have afforded not only a quantitative advantage (more intensive training) for letters but also a qualitative one, thus, increasing the relative saliency of letters by presenting the same letters in the context of different words.

The effect of the enlarged training set on improving the transfer to new words composed of the original letters supports previous findings showing that variable practice leads to better generalization in motor and non-motor tasks [1,54,64,74,75]. However, the claim of the 'variable practice' hypothesis is that the increased variability improves the generalization by involving a higher, more abstract, level of representations [1]. The current findings suggest that at least in early stages of reading acquisition, the improved transfer following the more "variable" training may be the result of learning to recognize the more basic units that are common to a larger number of items, rather than learning to recognize specifically the trained items.

We have previously shown that the specifics of a given task (task demands) rather than just the stimulus set may determine whether effective letter learning will occur [5]. Moreover, the results suggested that letter knowledge acquired in the practice of one task was not used in the context of a different task, concurrently practiced with the very same stimulus set (i.e. letter decoding did not occur in a visual matching task, even for words from the explicit training condition). The dependence of letter decoding on task demands was shown in a priming study in skilled readers [36]. Again, these findings suggest that letters were not automatically analyzed during word recognition, but only when their relative effectiveness for task performance was high. Our results are consistent with behavioral and neuroimaging findings of perceptual and motor learning studies, showing that the locus of learning related changes in brain representations is dependent on the specific requirements of the task, [42,69].

### *4.4. Implicit vs. Explicit instruction*

Our results show that some individuals may, under specific conditions, acquire phonological decoding from training on whole words, as suggested by previous models and shown by studies in children [27,57,78,79,82]. Moreover, the dependence of letter decoding acquisition on very specific training conditions, and on its usefulness for the task, may account for studies showing that letter knowledge was not acquired spontaneously from training on whole words [10,12,14,26,39,41,71]. Implicit acquisition of letter decoding was found to be less efficient than explicit training in terms of both the transfer to new words composed of the original letters, and the resistance to forgetting after a long delay. These results suggest that explicit instruction on component subunits prior to training may result in more robust and stable changes in brain representations during training. These findings support studies showing that explicit instruction on phonological decoding enhanced reading acquisition ([2,4,13,30,31,83], and see Ref. [73] for review). The performance of participants with high implicit letter knowledge suggests that the process of letter decoding slows reading, whether acquired explicitly or implicitly. The hypothesis that implicit learning would be advantageous compared to explicit learning in terms of processing speed, since it is more automatic and less dependent on working memory [1,60,76], may need amendment. Brooks and Miller [8], who trained subjects on reading artificial script in explicit, implicit and arbitrary training conditions, found that reading in the implicit condition was faster than in the explicit condition. However, in the Brooks and Miller study there were no indications that letter knowledge was acquired in the implicit condition, since no advantage was found for the implicit condition compared to the arbitrary condition in the transfer to new words. In the current study, we were able to show that the shorter RT in the implicit compared to the explicit condition was due to participants who did not acquire implicit letter knowledge.

### *4.5. The contribution of procedural and declarative knowledge to reading acquisition*

The results of the current and previous studies can be accounted for by the notion that different effective units of the training experience were learnt in each condition, both at the procedural and declarative levels [25]. From this perspective, performance in all training conditions would be initially dependent on declarative knowledge. However, with repeated experience, specific routines for task performance can be set, with the triggering of procedural learning mechanisms in all three training conditions. In the arbitrary condition, the initial declarative knowledge presumably consisted of word-specific representations (not necessarily whole words [5]), and a word-specific recognition routine was formed in the process of training. In the explicit condition, both the words and the letters were represented in declarative knowledge and both a letter decoding routine and a word recognition routine, were formed with training. In the implicit condition, the initial declarative knowledge consisted only of word-specific representations, thus it was to be expected that a word-specific recognition routine would evolve through training. However, only in the subgroup with subsequent high-letter-knowledge, two routines were formed with repeated experience, a letter-decoding routine and a word-recognition routine. This conjectured letter-decoding routine had presumably evolved implicitly from the repeating occurrence of regularities in the input [42,55].

We propose that the word-specific recognition routine evolved at a slower rate in all three conditions, and was therefore incomplete by the end of training. This was due to the relatively smaller number of repetitions on each word-unit during training, compared to six times as many repetitions afforded to the letter decoding routine. The latter was, therefore, more advanced by the end of training. This notion provides a parsimonious explanation for the advantage of the explicit condition over the arbitrary condition in long-term retention as well as following the initial training session, because the arbitrary condition can be considered as entirely dependent on the word-recognition routine.[2] Hence, the performance in the explicit condition may rely on a larger contribution from procedural memory mecha-

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[2] Although the declarative knowledge was not tested in the delayed session, participants' spontaneous report that they "do not remember anything" lends some support to the conjecture that their highly preserved performance in the delayed session reflected mainly procedural knowledge.

nisms, while performance in the arbitrary condition may have involved a larger declarative component. Ullman et al. [80,81] has recently argued that rule-like behavior (in regular verbs) involved procedural learning associated with the frontal and basal ganglia circuit, while exemplar-based lexical processing (of irregular verbs) involved declarative memory associated with medio-temporal regions. Our results, however, suggest that both the word-specific recognition and the letter decoding routines became proceduralized with repetitions. In similarity to the learning of perceptual and motor skills, improvement in all training conditions required time, multiple sessions and numerous repetitions (besides being well fitted by power functions) ([1,32,37,42,51,70], but see Refs. [31,40]). Hence, we suggest that the contribution from procedural and declarative processes to letter decoding and word recognition is dynamic and dependent on the amount of practice, rather than being a static characteristic of each type of knowledge. We would, therefore, predict that the difference between the long-term retention in the explicit and arbitrary conditions may disappear given sufficient word repetitions. This notion is in accord with a number of studies of second language acquisition suggesting that explicit (declarative) grammar knowledge is transformed into qualitatively different procedural knowledge, and subsequently a gradual 'automatization' process takes place [23,52,70].

## 5. Conclusions

Our results suggest that training on alphabetical words following explicit letter instruction can result in effective letter knowledge, as well as in effective word-specific pattern recognition. Furthermore, we have shown that letter knowledge could be acquired implicitly from training on alphabetical whole words, under specific conditions, by some individuals. The implicitly acquired letter knowledge, evident in task performance, was independent of declarative letter knowledge, suggesting that letter knowledge may be represented in the brain by both procedural and declarative mechanisms. Overall, our results show that letter decoding resulted in more accurate but slower reading regardless of the explicitness of the instruction, and that implicit training had no advantage over explicit training. The results of our current and a previous study [5] show that letter decoding in both explicit and implicit training conditions may evolve depending on constraints imposed by task demands and the structure of the training experience. However, even under conditions that presumably afford clear advantage for word segmentation, participants may acquire word-specific pattern recognition as well as letter knowledge in both explicit and implicit training conditions. We propose that brain mechanisms associated with both procedural and declarative learning contribute to letter decoding as well as word recognition routines, and that both routines can become proceduralized given sufficient practice.

More generally, our results suggest that the level of brain representations that is affected by training is determined by task relevance. The evolution of a segmentation routine for segmenting the presented items into smaller subunits, in both explicit and implicit training conditions, may depend on the cost-effectiveness of segmentation given the specific task requirements. Increased variability in the set of training items may enhance segmentation and thus lead to more effective transfer of learning gains to novel stimuli that share these same segments. Furthermore, our results suggest that an increased number of repetitions during training may result in a greater reliance on procedural learning for the performance of the task, and consequently, a better preservation of the learning gains in the long term. Finally, our findings show that implicit training instruction did not have an advantage for learning compared to explicit instruction.

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