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Offline Improvement in Learning to Read a Novel Orthography Depends on Direct Letter Instruction

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Abstract

Improvement in performance after the end of the training session, termed ''Offline improvement,'' has been shown in procedural learning tasks. We examined whether Offline improvement in learning a novel orthography depends on the type of reading instruction. Forty-eight adults received multisession training in reading nonsense words, written in an artificial script. Participants were trained in one of three conditions: alphabetical words preceded by direct letter instruction (Letter-Alph); alphabetical words with whole-word instruction (Word-Alph); and nonalphabetical (arbitrary) words with whole-word instruction (Word-Arb). Offline improvement was found only for the Letter-Alph group. Moreover, correlation with a standardized measure of word reading ability showed that good readers trained in the Letter-Alph group exhibit greater Offline improvement, whereas good readers trained in the Word-Arb group showed greater Within-session improvement during training. These results suggest that different consolidation processes and learning mechanisms were involved in each group. We argue that providing a short block of direct letter instruction prior to training resulted in increased involvement of procedural learning mechanisms during training.

Keywords: Procedural learning; Reading acquisition; Transfer; Artificial language; Consolidation; Declarative memory

1. Introduction

Reading acquisition should rely on both procedural and declarative learning mechanisms. Procedural learning, the acquisition of skilled performance on a task, requires extraction of recurring elements from repeating events and relies on striatal–thalamic–cortical loops (Eichenbaum, 2003; Gabrieli, 1998; Mishkin, Malamut, & Bachevalier, 1984; Squire &

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Zola, 1996). Declarative knowledge, knowledge of facts and events, which involves the detection of characteristics of a given stimulus in a single event (Squire, 2004), relies on the hippocampus and parahippocampal regions that mediate changes in other cortical regions (Eichenbaum, 2003; Gabrieli, 1998). Although they rely on (partly) distinct neural circuits, information acquired initially by the rapid declarative system may be gradually proceduralized with recurring of analogous events (Aizenstein et al., 2004; Anderson, 1982; Marshall & Born, 2007; Packard & McGaugh, 1996; Poldrack & Packard, 2003; Poldrack et al., 2001; Schendan, Searl, Melrose, & Stern, 2003).

After years of dispute about the most effective method for reading instruction (Foorman, 1995), there is growing evidence in the last decade for the benefits of including systematic letter-sound correspondence instruction, in addition to instruction of whole words, for reading acquisition in both reading disabled and typically developing children (Ehri, Nunes, Stahl, & Willows, 2001; de Graaff, Bosman, Hasselman, & Verhoeven, 2009; Shapiro & Solity, 2008). This advantage raises the possibility that explicit teaching of letter-sound correspondence triggers a different learning mechanism compared with methods that emphasize larger units, such as whole words. Both procedural and declarative learning presumably interact during reading acquisition. Skilled readers of all orthographies have conscious declarative knowledge about the mapping of orthography to phonology in units of various sizes (i.e., individual letters, letter clusters, and whole words). However, skilled fluent reading is acquired gradually, as a function of repeated experience, which is the characteristic of rote learning and skill acquisition (Karni, 1996). In previous studies, we used an artificial orthography to examine the effects of instruction method on reading acquisition in adults (Bitan & Karni, 2003, 2004). We found an advantage for direct letter instruction not only for reading trained items and generalizing to untrained stimuli but also in long-term retention 6 months after training (Bitan & Karni, 2004). We suggested that letter instruction resulted in greater reliance on procedural learning compared with whole-word instruction, perhaps due to the greater number of repetitions on letters compared with words. Our functional magnetic resonance imaging (fMRI) study showed that distinct brain regions were involved in reading trained words depending on whether they were learned through letter versus whole-word instruction (Bitan, Manor, Morocz, & Karni, 2005).

In the current study, we use an artificial orthography to examine the effects of instruction method on the consolidation of knowledge after the end of training, that is, Offline improvement. Previous motor and perceptual learning studies showed post-training improvement in performance, measured a period of time after training, when compared with performance immediately after training (Cohen, Pascual-Leone, Press, & Robertson, 2005; Fenn, Nusbaum, & Margoliash, 2003; Fischer, Hallschmid, Elsner, & Born, 2002; Gaab, Paetzold, Becker, Walker, & Schlaug, 2004; Gervan & Kovacs, 2010; Karni, Tanne, Rubenstein, Askenasy, & Sagi, 1994; Korman, Raz, Flash, & Karni, 2003; Kuriyama, Stickgold, & Walker, 2004; Stickgold, Hobson, Fosse, & Fosse, 2001; Walker, Brakefield, Morgan, Hobson, & Stickgold, 2002; Wright & Sabin, 2007). This process of consolidation by which a fragile memory transforms into a robust trace (Robertson, Pascual-Leone, & Press, 2004; Walker, 2005) has been suggested to depend on sleep (Fischer, Wilhelm, & Born, 2007; Fischer et al., 2002; Karni et al., 1994; Korman et al., 2007; Maquet et al., 2004; Plihal &

Born, 1997; Rauchs, Desgranges, Foret, & Eustache, 2005). Although sleep also enhances consolidation in hippocampus-dependent declarative learning (Backhaus et al., 2007; Born, Rasch, & Gais, 2006; Drosopoulos, Wagner, & Born, 2005; Marshall, Helgadottir, Molle, & Born, 2006; Marshall, Molle, Hallschmid, & Born, 2004; Peigneux et al., 2004; Plihal & Born, 1997; Rasch, Buechel, Gais, & Born, 2007), its effect is often seen in reducing forgetting that normally occurs after training, rather than as a performance improvement in the next session (Drosopoulos et al., 2005; Ellenbogen, Hulbert, Stickgold, Dinges, & Thompson-Schill, 2006; Gais, Lucas, & Born, 2006; Marshall & Born, 2007). These studies imply that while Offline improvement is expected in procedural learning, greater decay and forgetting is expected for declarative learning (Marshall & Born, 2007). In the current study, we examined whether providing direct letter instruction for individuals learning to read a new orthography affects consolidation processes reflected in Offline improvement.

2. Materials and methods

2.1. Participants

Forty-eight Northwestern University students (18–30 years; 16 males) participated. All were native English speakers with normal linguistic and reading skills and no diagnosis of learning disabilities, attention deficit, neurological, or psychiatric disorders. Their adequate reading and learning abilities were confirmed by four standardized tests (WJ-III, Woodcock, McGrew, & Mather, 2001): ''Letter-Word Identification'' and ''Word Attack'' subtests, measuring decoding ability of words and nonwords, and ''Analysis Synthesis'' and ''Concept Formation'' subtests from the cognitive abilities scale, for assessing learning abilities. Participants were randomly assigned to three groups (Letter-Alph, Word-Alph, and Word-Arb) with balanced ages and gender across groups, and no significant differences in standardized tests scores (see Table 1).

Table 1
Age, gender, and standard scores by groups

Group	Mean Age		Concept Formation	Analysis Synthesis	Word Identification	Word Attack
Word-Arb n = 16 (6 males)	21.6	*M*	111.2	117.1	118.9	108.8
		SD	7.8	19.2	5.7	7.3
Letter-Alph n = 16 (4 males)	19.8	*M*	109.4	113.8	116.0	107.9
		SD	7.5	13.9	6.5	8.4
Word-Alph n= 16 (6 males)	20.1	*M*	110.4	114.4	119.8	110.7
		SD	9.2	15.9	6.3	5.4
Total N = 48	20.5	*M*	110.4	115.1	118.2	109.1
		SD	8.0	16.2	6.3	7.1

Note. Standard scores for the tests taken from the Woodcock Johnson III battery for participants in the three training groups.

2.2. Stimuli

Stimuli and procedure were modified from a previously used paradigm (Bitan & Karni, 2004). Modifications included better control for visual complexity of the orthography across groups, using a between subject design, testing generalization at three time points during training, adding auditory presentation of correct pronunciations, and adaptation for English speakers.

2.2.1. Trained set

Twelve nonwords written in a novel orthography, in which a pair of symbols represents one letter, and six symbols in different permutations create all letters (see Table 2). This orthography was designed to enhance demands on segmentation processes reflecting the challenges in learning to read natural orthographies with different grain sizes. Nonwords were composed of two consonants and one vowel in all possible syllable structures (CVC, VCC, CCV), and each phoneme repeated six times in the list of 12 nonwords. In the alphabetical groups (Letter-Alph and Word-Alph), each nonword is represented using a consistent correspondence of grapheme (letter) to phoneme, whereas in the Word-Arb group the correspondence of graphemes to phonemes differs across nonwords (see Table 2). Word-Arb was included to determine whether participants relied entirely on whole-word identification in Word-Alph, in which case the pattern of results should be similar for the two conditions. Pronunciation of stimuli was based on the CELEX database (Baayen, Piepenbrock, & Gulikers, 1995), with two pronunciations for each vowel depending on its position to increase the similarity to English.

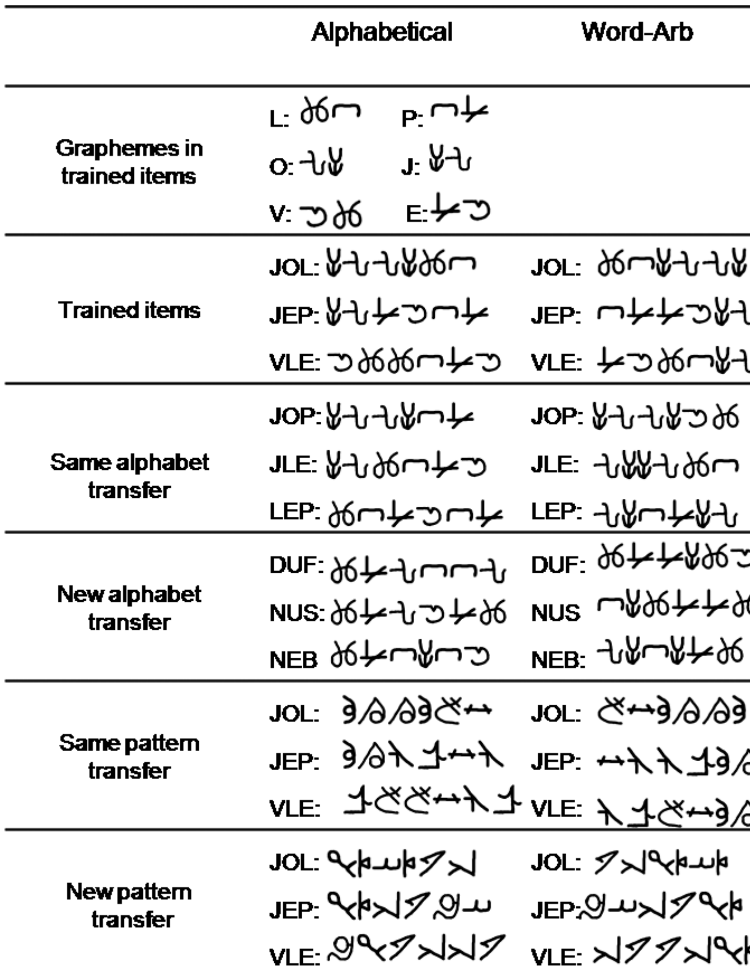
2.2.2. Transfer tests

The transfer of learning gains to novel stimuli was tested in four types of transfer tests (see Table 2): (1) Same-Alphabet transfer consists of new nonwords written with the *same alphabet* and same symbols. (2) New-Alphabet transfer consists of new nonwords written with a *new alphabet* and the same symbols. A comparison of Same-Alphabet versus New-Alphabet transfer serves as an indicator of alphabetical knowledge. (3) Same-Pattern transfer consists of the trained nonwords written with new symbols arranged in the *same visual pattern* of symbol repetitions and internal symmetries as the trained nonwords. (4) New-Pattern transfer consists of the trained nonwords written with new symbols arranged in a *new visual pattern*. A difference between Same-Pattern and New-Pattern transfer is an indicator of visual pattern knowledge. Three sets of lists, 12 nonwords in each list, were created for each transfer type in order to examine transfer in different points during training.

2.3. Procedure

Participants were trained on six sessions, spaced 1–3 days apart (see Fig. 1). The stimuli were presented on a PC screen, 60 cm from the participant. Stimulus presentation data recording were carried out using E-Prime 1.0 software (Psychology Software Tools, Pittsburgh, PA).

Table 2
Examples of stimuli



Note. Examples of graphemes and nonwords used in training and in the four transfer testing conditions in the alphabetical (Letter-Alph and Word-Alph) and arbitrary (Word-Arb) conditions.

2.3.1. Session 1

All groups received a ''Whole-word instruction'' block, in which participants were presented with each target nonword written in the novel orthography together with its corresponding phonological translation to Latin letters below for 2,000 ms (Fig. 1B). Participants simultaneously heard the correct pronunciation through headphones and had to repeat it and memorize the association. The Latin letter translation was included to maximize learning. Nonwords appeared twice in a fixed order (24 trials).

A ''Letter instruction'' block was given prior to the whole-word instruction block only in Letter-Alph. Here, individual letters in the novel orthography were presented with their

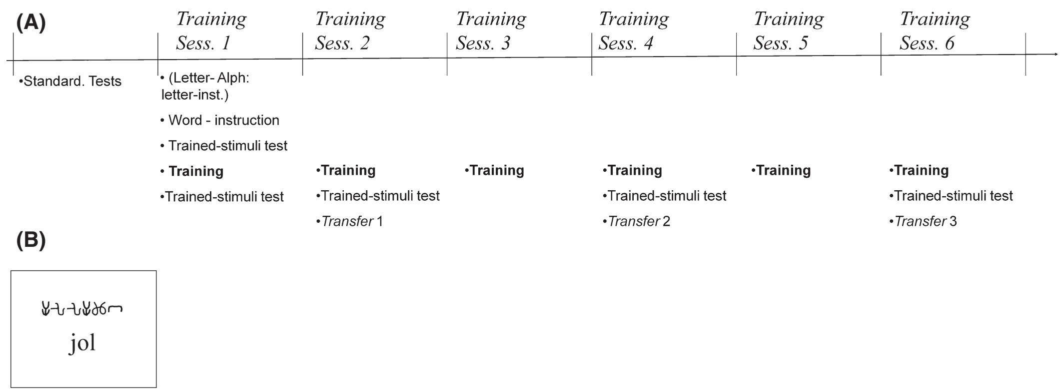


Fig. 1. (A) Timeline of the experiment; (B) example of display during training.

corresponding Latin letter translation for 2,000 ms. Subjects had to pronounce the phoneme and memorize the association. Letters appeared four times in a fixed order (24 trials). Instruction blocks were given during the first training session only.

A ''Test block'' of 48 trials followed, in which pairings of target nonword and Latin letters translation appeared for 800 ms (Fig. 1B). Half of the pairings were correct and participants had to indicate by button press whether pairing was correct. Violations in incorrect pairings were equally spread across letters, so all letters in the nonword had to be processed. This ''test block'' was included as an estimate for performance before the beginning of training to serve as a baseline for normalizing the effects of transfer tests. This test was followed by 7 training blocks, 48 trials each (336 trials total). Training blocks were similar to the test block except that participants received an auditory feedback when they made a mistake.

2.3.2. Sessions 2–6

These sessions included seven training blocks (see Fig. 1). In Sessions 2, 4, and 6, training was followed by a test block and then four transfer tests (one of each type: Same-Alphabet transfer, New-Alphabet transfer, Same-pattern transfer, and New-pattern transfer, 48 trials each). Transfer tests were preceded by a ''Whole-word instruction block'' for the untrained stimuli, so that participants were able to perform the test even for a new alphabet. No ''Letter instruction block'' was given for the transfer stimuli in any group. The order of the four types of transfer tests was balanced across individuals and fixed for each individual across sessions.

2.4. Data analysis

Because we measure proportion, which is limited by 1.0 and is asymmetrically distributed especially in late sessions, we used the Arcsine transformation on the raw accuracy measured in each block. All reported differences and ratios in accuracy were calculated on the transformed data. Our measure for ''Offline Improvement'' was calculated as the difference in accuracy between performance in the first block of each session and the last block of the previous session. In order to account for learning gains that occur between any consecutive training blocks, Offline improvement was compared with a measure of ''Within-session improvement'' calculated as the mean difference between all pairs of consecutive blocks in a given session.

In order to test the unique contribution of Offline vs. Within-session improvement, we fitted a curve to the data from each group separately. Using the Akaike Information Criterion (AIC) for goodness of fit, we tested whether the addition of five dummy variables coding for between-session gains (one for each session) had a significant contribution to model fit beyond a linear curve, and compared it with the contribution of six dummy variables coding for improvement in the first pair of blocks within each session (block 2–block 1). Four models were compared, which were based on a linear curve: (1) with no dummy variables; (2) with five dummy variables coding for enhanced Offline improvement; (3) with six dummy variables coding for enhanced improvement from block 1 to block 2 within each session; and (4) with all the above 11 dummy variables.

To test generalization, we used a normalized transfer index that reflects the proportion from the concurrent gain in performance on trained items calculated as follows:

$$\begin{aligned}&\mathit{Transfer\ Index}\\&=\frac{(\mathit{Accuracy\ on\ transfer\ test} - \mathit{Accuracy\ on\ trained\ items\ before\ training})}{(\mathit{Concurrent\ accuracy\ on\ trained\ items} - \mathit{Accuracy\ on\ trained\ items\ before\ training})}\end{aligned}$$

In this equation, ''accuracy on trained items before training'' was measured by the ''Test block'' conducted after the instruction block(s) but before the training blocks (see above); therefore, performance may be above chance level. This procedure is identical to the measurement in the transfer test, in which participants' performance is measured after a block of instruction but with no training. Normalization of transfer to the gain in performance on trained items was used in order to account for differences in performance on the transfer test that are due to differences in performance on trained items. For example, poor performance on a transfer test in light of high gains on trained items is indicative of low generalization of learning. In contrast, individuals with poor performance on transfer tests with low gains on trained items may simply exhibit poor learning rather than lack of generalization.

3. Results

Accuracy and reaction time (RT) during training improved in all three training conditions (Fig. 2). GLM repeated-measures analyses were conducted on accuracy and RT (6 Sessions × 7 Blocks × 3 Groups). Accuracy showed significant main effects of session, $F(5,225) = 168.6$, $p < .001$, and block, $F(6,270) = 16.4$, $p < .001$, and a marginally significant interaction of group by session, $F(5,225) = 1.87$, $p = .05$. This interaction was followed by separate analyses within each session. Only in Session 1, this analysis

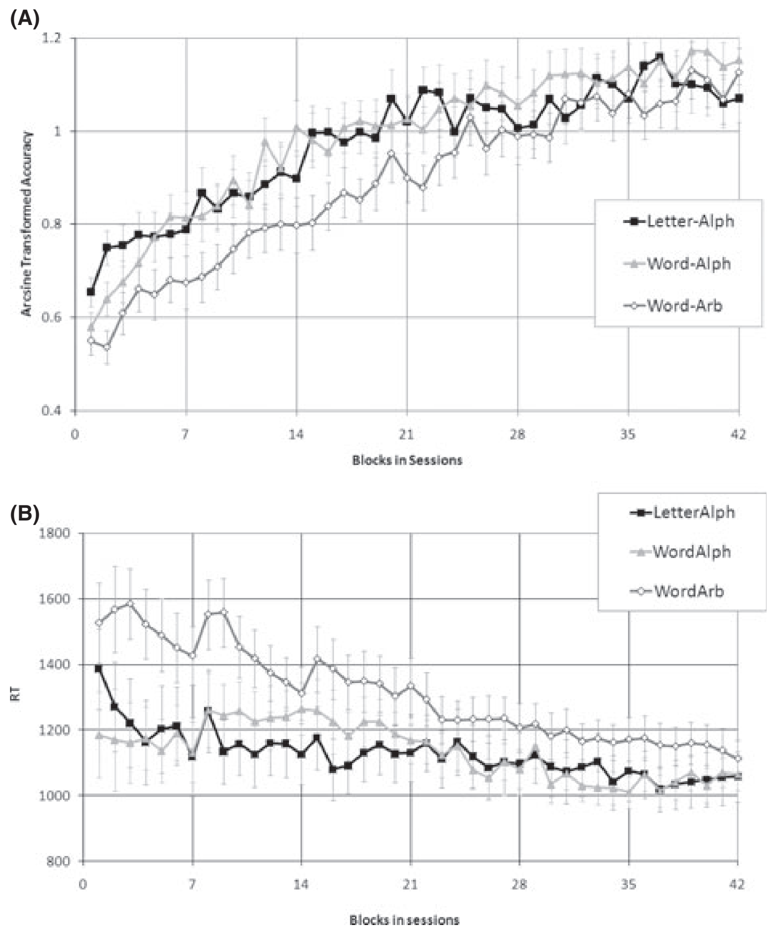


Fig. 2. Performance during training in the three groups. Accuracy (A) and reaction time (B) are plotted per block, with seven blocks per session. Error bars indicate standard errors.

revealed a significant effect of group, $F(2,45)=3.26$, $p < .05$. Post hoc comparisons with Tukey correction for multiple comparisons showed significantly higher accuracy in Letter-Alph compared with Word-Arb ($p = .044$). RT analysis showed a significant effect of session, $F(5,225) = 10.6$, $p < .001$, and block, $F(6,270) = 8.7$, $p < .001$, with no significant main effect or interactions with group. No speed accuracy tradeoff was observed.

3.1. Offline improvement versus Within-session improvement

Fig. 3A shows Offline and Within-session improvement in Sessions 1–5 (Offline improvement cannot be measured for the last session). A GLM analysis was conducted with 2 Types of gain (Offline vs. Within-session improvement) × 5 Sessions × 3 Groups. This revealed a significant interaction of gain and group, $F(2,41) = 4.23$, $p < .05$. A separate

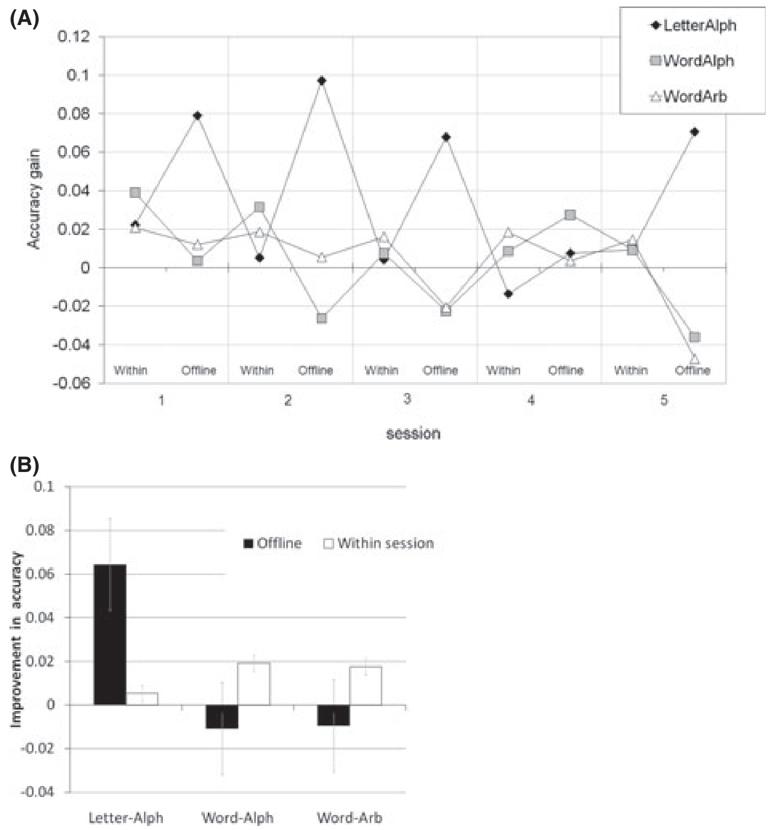


Fig. 3. (A) Offline improvement and Within-session improvement in the three groups. Offline improvement is the gain in accuracy from the last block in each session to the first block of the next session. Within-session improvement is the average difference between consecutive blocks within each session. (B) Offline improvement and Within-session improvement averaged across sessions.

analysis within each group showed a significant difference between Offline improvement and Within-session improvement only for Letter-Alph, $F(1,15) = 5.34$, $p < .05$ (see Fig. 3B). To further test the interaction of group and gain, separate analyses were conducted for each type of gain. The analysis of Offline gains showed a significant effect of group—$F(2,45) = 4.18$, $p < .05$ corrected for two comparisons. Tukey post hoc comparisons showed significant differences between Letter-Alph and Word-Arb ($p = .04$) and between Letter-Alph and Word-Alph ($p = .039$). The analysis of Within-session improvement did not show a significant group effect, $F(2,45) = 3.78$, $p > .05$, corrected for two comparisons.

In order to examine whether group differences specific to Offline improvement could be accounted for by differences in the stability of the two measurements (namely, Offline- vs. Within-session improvement) or greater fatigue in the Letter-Alph group, we conducted a GLM analysis breaking down Within-session improvement into individual pairs of consecutive blocks. This resulted in analysis of 7 Pairs (6 Pairs Within-session and 1 indicating Offline improvement) × 5 Sessions × 3 Groups. This analysis showed a significant interaction of Pair × Group, $F(12,270) = 2.17$, $p < .05$, which was followed by the analysis of Pairs × Sessions within each group. For Letter-Alph, this analysis revealed a significant effect of Pair, $F(6,90) = 2.26$, $p < .05$, and specific contrasts show that only the Offline improvement was significantly different from the mean, $F(1,15) = 5.34$, $p < .05$. Analysis within other groups showed no significant effect of Pair—$F(6,90) = 1.36$ and 1.22, $p > .05$; for Word-Arb and Word-Alph, respectively (see Fig. 4). Fig. 4 also shows that effects of fatigue cannot explain the greater Offline improvement in the Letter-Alph group: (a) initial gains in the Letter-Alph group are not larger than later gains within the session. (b) GLM analysis within Pair did not show a significant difference between groups for the ultimate or penultimate pairs of blocks (7–6 and 6–5), $F(2,45) = 1.4$, 0.65, respectively, $p > .05$.

To test whether Offline and Within-session improvement are differentially recruited in individuals with good versus poor reading ability, we tested in each group the correlation of Offline and Within-session improvement (averaged across sessions) on one hand with the Letter-Word Identification test (LWID) on the other hand. In Letter-Alph, LWID was positively correlated with Offline improvement ($r = .49$, $p < .05$) but not with Within-session improvement ($r = -.29$, $p = ns$) (see Fig. 5A). However, Word-Arb showed the opposite pattern: LWID was positively correlated with Within-session improvement ($r = .60$, $p < .01$) but not with Offline improvement ($r = -.39$, $p = ns$) (see Fig. 4B). No correlations were found for Word-Alph.

In order to test the contribution of Offline improvement to explaining performance in the Letter-Alph group, we tested four models based on a linear curve. Using AIC, we tested the contribution of adding the following dummy variables over a simple linear model: (a) enhanced Offline improvement, (b) enhanced improvement between the first pair of blocks within session, or (c) both. Table 3 shows that the model with Offline variables for Letter-Alph indicates a better fit than the simple linear model or the model with only Within-session variables. However, this model shows that only the coefficients for Offline

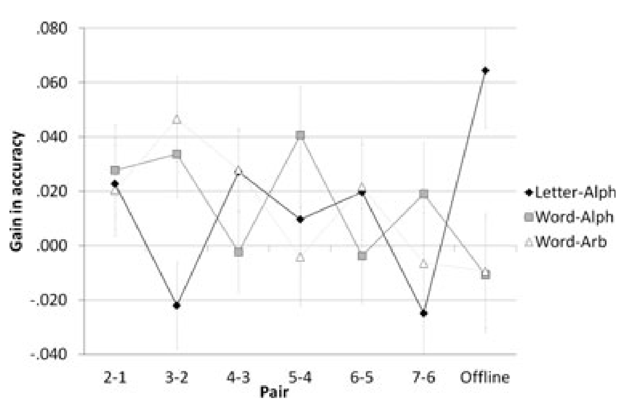


Fig. 4. Gain in accuracy between consecutive blocks Within-session (blocks 1–7) and between sessions (Offline improvement). Gains are averaged across sessions.

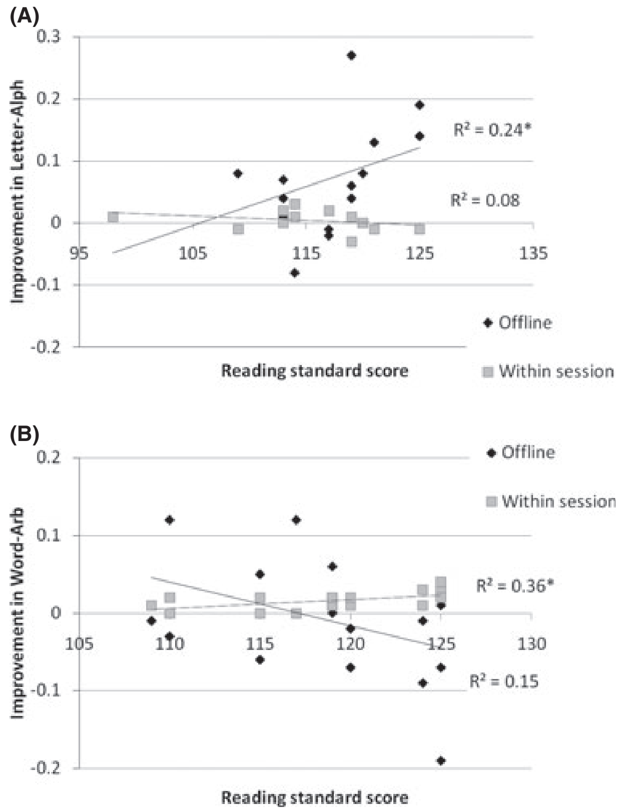


Fig. 5. Correlation between reading standard score and improvement (Offline improvement and Within-session improvement, each averaged across sessions) in Letter-Alph (A) and Word-Arb (B) groups. *Significant correlation. R^2 is presented.

improvement in the first and second sessions were significant (see Fig. S1). When including both Offline and Within-session variables in the same model, the coefficients for Offline improvement in the first and second sessions remain significant, in addition to Within-session gain in the first pair of blocks in the first session. In contrast to Letter-Alph, Table 3 shows that, for Word-Alph and Word-Arb, most offline coefficients are negative, indicating reduction rather than improvement between sessions (see Fig. S1). The positive ''offline sess. 1'' coefficient in Word-Alph appears to actually reflect a within-session gain because this variable is no longer significant in the model that includes both types of variables.

3.2. Transfer tests

Fig. 6 shows the transfer index calculated for each transfer test at each time point, whereas Fig. 7 shows the differences between these indices indicating Alphabetic and Pattern knowledge. A GLM analysis, conducted with 2 Types of knowledge (Alphabetic vs. Pattern knowledge) × 3 Time points × 3 Groups showed a significant interaction between

Table 3
Goodness of fit estimates and variable coefficient for model curves fitted to each group

Model Type	Coefficient	Letter-Alph		Word-Alph		Word-Arb	
		AIC	Coeff. *t*	AIC	Coeff. *t*	AIC	Coeff. *t*
Linear		−622.3		−707.5		−865.4	
Linear + 5 Offline		−660.4		−765.3		−877.5	
variables	Offline sess. 1		**3.78***		**2.86***		0.58
	Offline sess. 2		**4.19***		−0.59		−0.53
	Offline sess. 3		0.72		**−2.57**		−1.39
	Offline sess. 4		−0.4		**−2.56**		**−2.17**
	Offline sess. 5		0.57		**−3.77***		**−3.86***
Linear + 6 First pair		−651.9		−765.1		−868.2	
within session	First pair sess. 1		**2.59***		**3.59***		1.49
	First pair sess. 2		**1.99**		**3.69***		**2.47**
	First pair sess. 3		**2.66***		−0.12		1.25
	First pair sess. 4		−1.47		−0.88		0.93
	First pair sess. 5		−0.53		−1.57		−0.57
	First pair sess. 6		−1.48		**−2.01**		−1.38
Linear + all 11		−646.9		−748.8		−851.3	
variables	Offline sess. 1		**2.34**		0.81		−0.01
	Offline sess. 2		**2.94***		0.5		−0.63
	Offline sess. 3		1.9		−1.51		−1.77
	Offline sess. 4		−1.02		−1.02		−1.24
	Offline sess. 5		1.55		**−1.97**		**−2.2**
	First pair sess. 1		**2.83***		**3.18***		1.03
	First pair sess. 2		−0.03		1.33		1.01
	First pair sess. 3		0.07		−0.72		0.87
	First pair sess. 4		−1.47		0.41		1.55
	First pair sess. 5		1.32		−0.35		0.21
	First pair sess. 6		−1.38		−0.06		0.24

Note. AIC, Akaike Information Criterion for goodness of fit (smaller is better); Coeff. *t*, *t*-value of variable coefficient. Bold $p < .05$; bold*$p < .01$.

the type of knowledge and group, $F(2,45) = 6.8$, $p < .01$. A separate analysis within each type of knowledge showed a significant effect of group for Alphabetic knowledge, $F(2,45) = 12.48$, $p < .001$, but not for Pattern knowledge, $F(2,45) = 1.83$, $p > .05$. Tukey post hoc comparisons between groups for Alphabetic knowledge showed significantly greater alphabetic knowledge for Letter-Alph compared with Word-Alph ($p = .013$) and compared with Word-Arb ($p = .000$).

To examine the evolution of the acquired knowledge during training, we calculated the difference between the first and last time points for each type of transfer (Fig. 8). A GLM analysis was conducted on the difference between first and last time points, with 4 Types of transfer test × 3 Groups. The analysis showed a significant effect of group, $F(2,45) = 5.61$. $p < .01$, and no interaction between group and transfer type, $F(6,135) = 1.77$, $p > .05$. Tukey post hoc comparisons revealed a significant difference between Letter-Alph and

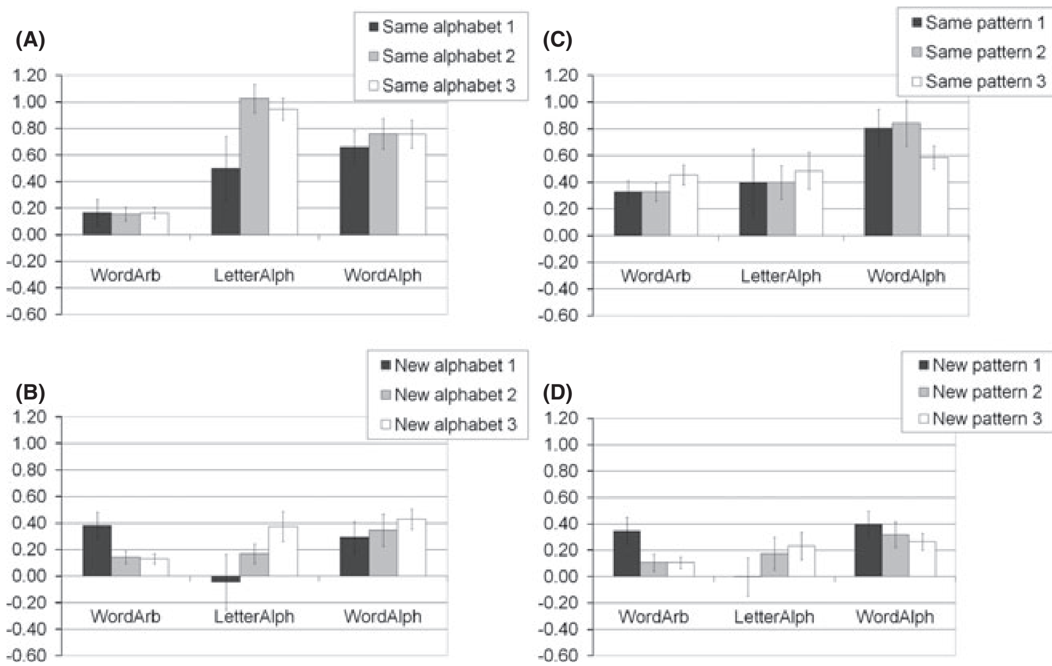


Fig. 6. Index of accuracy on the transfer tests (see text for definitions) at three different time points in training (1, 2, 3).

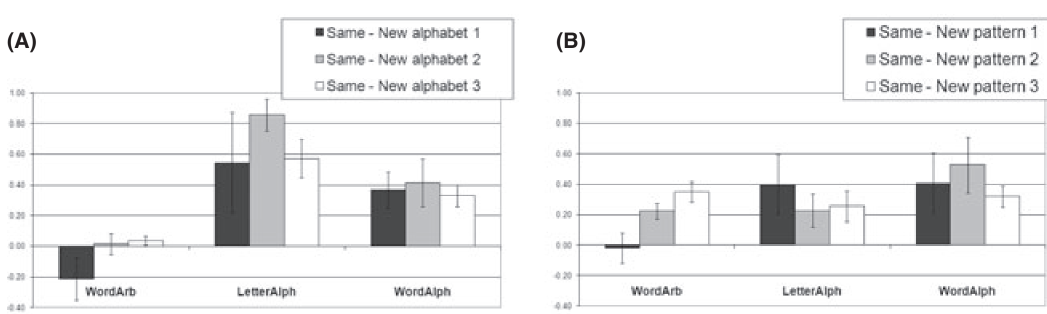


Fig. 7. Alphabetical knowledge and pattern recognition knowledge at three different points in training for all groups. Alphabetical knowledge (A) is calculated as the difference between the Same-Alphabet and New-Alphabet transfer. Pattern recognition (B) is calculated as the difference between Same-pattern and New-pattern transfer.

Word-Alph (p = .032) and between Letter-Alph and Word-Arb (p = .009), indicating that overall the increase in performance on the transfer tests from the first to last test was greatest for the Letter-Alph. One-sample t-tests conducted within each group showed for Letter-Alph

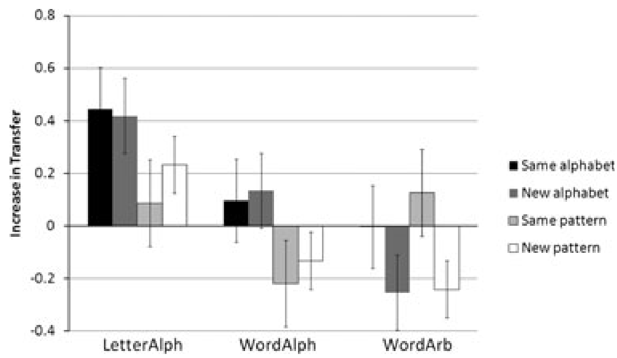


Fig. 8. Increase in transfer from second to the last training session, calculated by the difference in transfer index in the sixth minus second session. Negative values indicate a decrease in the amount of transferred knowledge from early to late stages of training.

a significant increase in Same-Alphabet transfer, $t(15) = 1.87$, $p < .05$; New-Pattern transfer, $t(15) = 2.09$, $p < .05$; and New-Alphabet Transfer, $t(15) = 2.14$, $p < .05$. For Word-Arb, there was a significant decrease in New-Alphabet transfer, $t(15) = -2.41$, $p < .05$, and in New-pattern Transfer, $t(15) = -1.97$, $p < .05$. For Word-Alph, a significant decrease was found in Same-pattern transfer, $t(15) = -1.9$, $p < .05$.

Finally, to test whether Offline improvement is associated with alphabetic knowledge, we correlated, within each group, Offline or Within-session improvement (averaged across sessions) with alphabetic knowledge in three time points. Only for Letter-Alph, alphabetic knowledge was positively correlated with Offline improvement ($r = .51$) and negatively correlated with Within-session improvement ($r = -.49$) in the second time point. However, this did not survive a correction for multiple comparisons. No such correlations were found in the other groups.

4. Discussion

Our results show that learning to read an alphabetical orthography following direct instruction on letters (Letter-Alph) resulted in higher accuracy on trained items compared with reading whole words in a nonalphabetical orthography (Word-Arb) only in the first training session. No difference was found between the two groups trained on the alphabetical orthography (Letter-Alph and Word-Alph). However, in spite of the overall similarity in performance, the groups differ in the amount of Offline improvement, namely, the gain in performance after the end of each training session. Participants in Letter-Alph showed significantly more Offline improvement compared with the two groups that received only whole-word instruction. Moreover, we found that reading skill (measured by a standardized word reading test) was correlated with a different type of gain in different groups. Good readers in the Letter-Alph group showed more Offline improvement, whereas good readers in the Word-Arb group showed larger Within-session improvement. Finally, testing the transfer of learning gains to untrained stimuli showed higher alphabetical knowledge for the Letter-Alph group compared with the Word-Alph group across all sessions. During training, participants in the Letter-Alph group also showed an increase in their ability to generalize their acquired knowledge to different novel orthographies, whereas knowledge acquired through whole-word instruction became increasingly specific.

4.1. Reading of trained items and Offline improvement

The advantage found for Letter-Alph compared with Word-Arb in reading trained items on the first training session suggests that, in the early stages of training, learning may be facilitated by focusing on smaller segments, rather than memorizing larger units. These results are consistent with findings from classroom studies showing the advantage of explicit instruction of letter-sound correspondences for beginning readers (Ehri et al., 2001; de Graaff et al., 2009; Rayner, Foorman, Perfetti, Pesetsky, & Seidenberg, 2001; Shapiro & Solity, 2008). Performance of participants in Word-Alph was not different from either of the two other groups. The relatively small differences in performance among groups may be due to the small number of items presented in training, which may facilitate whole-word identification.

More dramatically, participants in Letter-Alph showed greater Offline improvement compared with the groups with only whole-word instruction, especially after the first and second sessions. Moreover, although participants in Letter-Alph showed more Offline- than Within-session improvement, no Offline gains were found in the other groups. These differences in the time course of improvement suggest that consolidation processes in Letter-Alph are different from those in the other groups, perhaps due to different learning mechanisms involved during training. This notion of reliance on different learning mechanisms is supported by the finding that reading skill was correlated with different types of gains in the different groups, with critical contribution of Offline improvement in Letter-Alph, and of Within-session improvement in Word-Arb. When good readers are presented with the training material, they presumably converge on the most effective learning strategy afforded by the available information. Thus, these results support the conclusion that learning relied on different learning mechanisms in the two groups. Although both declarative and procedural learning processes were presumably involved in learning of all groups, we suggest that the greater contribution of Offline improvement in Letter-Alph indicates that learning in this group involves procedural learning processes more than learning in the other two groups.

Previous studies have shown that consolidation of procedural learning resulted in Offline improvement measured after a period of time in sleep (Cohen et al., 2005; Fischer et al., 2002; Jackson et al., 2008; Korman et al., 2003; Kuriyama et al., 2004; Robertson et al., 2004; Walker, 2005; Walker et al., 2002). Declarative memory is considered to be less robust and decay faster than nondeclarative processes (Allen & Reber, 1980; Reber, 1992; Tunney, 2003). It should be noted that consolidation of declarative memories also benefits from sleep (Born et al., 2006). However, rather than Offline improvement in performance, the benefit of sleep for hippocampal-related learning is typically manifested as increasing the chances of gaining insight from implicit training (Born et al., 2006; Ellenbogen, Hu, Payne, Titone, & Walker, 2007; Fischer, Drosopoulos, Tsen, & Born, 2006; Robertson & Cohen, 2006; Spencer, Sunm, & Ivry, 2006; Wagner, Gais, Haider, Verleger, & Born, 2004) or diminished decay on the day following the learning episode (Drosopoulos et al., 2005; Ellenbogen et al., 2006; Gais et al., 2006; Marshall & Born, 2007). A number of studies have shown Offline improvement in a task considered to rely on hippocampal-dependent declarative learning, namely, paired-associates learning (Marshall et al., 2006; Plihal & Born, 1997; Wilhelm, Diekelmann, & Born, 2008). However, even in these studies, we cannot be confident that Offline improvement was the result of the declarative component of learning because memory tasks are never purely declarative or procedural (Born et al., 2006). Previous studies have shown that declarative processes and hippocampal involvement may constitute the initial phases of skill acquisition (Aizenstein et al., 2004; Anderson, 1982; Marshall & Born, 2007; Nokes & Ohlsson, 2005; Poldrack & Packard, 2003; Robertson, 2009; Schendan et al., 2003). In all the above paired-associates studies (Marshall et al., 2006; Plihal & Born, 1997; Wilhelm et al., 2008), participants were repeatedly exposed to trained stimuli until they reached a predefined criterion. This repetition may have contributed to the proceduralization of learning, so that Offline improvement could have resulted from a procedural component. Another verbal learning task that showed Offline improvement was a multisession training on an artificial morphological rule, where the authors attribute it to procedural learning (Ferman, Olshtain, Schechtman, & Karni, 2009).

One possible account for the difference between groups in Offline improvement is greater retroactive interference in the whole-word reading groups (i.e., Word-Arb and Word-Alph) when compared with the Letter-Alph group. It has been shown that retroactive interference from subsequently encountered experiences can impede Offline improvement in motor skill-learning tasks (Balas, Netser, Giladi, & Karni, 2007; Dorfberger, Adi-Japha, & Karni, 2007). Interference may occur even if the intervening experiences are not similar to the newly learned task (Balas et al., 2007; Brown & Robertson, 2007; Wixted, 2004). It is speculated that, in the current study, learning in the Word-Alph and Word-Arb groups may have suffered greater interference from general everyday activities of university students such as reading and attending classes, because they require item-specific declarative learning. Studies using artificial grammar and paired associates paradigms show greater effects of retroactive interference in declarative compared with nondeclarative learning (Graf & Schacter, 1987; Tamayo & Frensch, 2007; Tunney, 2003). Finally, even if Offline improvement cannot be considered an exclusive marker of procedural learning, given the greater susceptibility of declarative learning to rapid decay and interference, procedural consolidation is more likely to manifest in Offline improvement and may thus explain the results of the current study.

Recent studies (Cai & Rickard, 2009; Rickard, Cai, Rieth, Jones, & Ard, 2008) questioned the effect of offline enhancement in motor sequence learning by showing that improvement in performance after sleep, typically shown in sleep studies in comparison with a ''wake'' group, diminishes when controlling for circadian effects and avoiding averaging across trials (which masks effects of initial forgetting). These factors cannot explain the findings of the current study, which show differential effects of Offline improvement in groups receiving the same training schedule and which differ only in the content of the first instruction block. Another factor that can account for Offline improvement is fatigue, which may decrease performance at the end of the session (Sheth, Janvelyan, & Khan, 2008). The effect of fatigue on offline gains is enhanced under massed training conditions when compared with spaced training (Rickard et al., 2008). The self-pacing of trials in the current study presumably enhanced participants' comfort and reduced effects of fatigue. Moreover, the analysis of pairs of blocks within each session is not the characteristic of fatigue and does not show evidence for greater fatigue in the Letter-Alph compared with other groups. Another potential explanation for performance improvement between sessions is continued rehearsal after the end of training, which may be more successful in Letter-Alph because of the smaller units. However, given the novelty of the characters used in the orthography, it is unlikely that participants would retrieve them in a free recall setting.

The results of the current study are consistent with our previous results showing better preservation of acquired knowledge following direct letter instruction, when measured 6 months after training (Bitan & Karni, 2004). The current findings further show that learning following letter instruction is not only more resistant to forgetting, but it actually improves after training. In both studies, the greater resistance to forgetting after direct letter instruction may result from greater reliance on procedural learning due to more repetitions on letter-size units compared with word-size units in training. If Offline improvement in Letter-Alph indicates procedural consolidation, it suggests that participants in this group reached a stage in which new routines for performing a trained task are established. Hauptmann, Reinhart, Brandt, and Karni (2005) suggest that the saturation of Within-session improvement and the appearance of Offline improvement mark a qualitative change in brain areas engaged in task performance early on. According to this notion, only when the best performance has been attained by available routines can new routines be established resulting in an Offline improvement in performance. This interpretation and the results of the current study are consistent with a previous fMRI study (Bitan et al., 2005) that used a similar training paradigm, and compared trained and untrained words (Same-Alphabet transfer) between groups. The results showed that only in the letter-instruction group did reading of trained words become independent of decoding processes evident in the left inferior frontal gyrus. In contrast, reading of alphabetic words in the group that received whole-word instruction did not achieve this stage of automatic fluent recognition, as they were still engaged in effortful decoding of trained words even after six training sessions. This incomplete automatization of trained words in Word-Alph may reflect lack of proceduralization.

4.2. Generalization

The results of the transfer tests are consistent with our previous studies (Bitan & Karni, 2003, 2004) in showing greater alphabetical knowledge in Letter-Alph when compared with Word-Alph, suggesting that direct letter instruction is more effective than incidental learning of letters for reading unfamiliar words. The current study also tested the evolution of knowledge generalization throughout training and showed greater increase in generalization for Letter-Alph compared with the other groups, even for novel orthographies. These results suggest that individuals that received letter instruction not only acquired knowledge of the mapping between graphemes and phonemes in the trained orthography but also learned to segment strings of novel symbols, a skill that could be applied to a broader range of orthographies. These results may imply that explicit instruction on letter-decoding in one language may facilitate learning to read in subsequently learned languages with similar orthographic structures. In contrast, generalization to novel orthographies decreased with training in Word-Arb, indicating that participants learned only item-specific information rather than general pattern identification strategies; thus, these could not be generalized to other orthographies. Their knowledge becomes increasingly specific to trained patterns during training. These findings are consistent with bilingual studies showing the effect of reading experience in the first language on the acquisition of reading in the second language (Holm & Dodd, 1996; Jimenez, Garcia, O'Shanahan, & Rojas, 2010).

One question that remains open is the relationships between declarative and procedural learning processes and the generalizability of the acquired knowledge. Although the general notion tends to view skills as general tools that may be applied in a wide range of contexts, learning theories have argued that procedural learning is specific for the trained stimuli and context, whereas declarative knowledge is more abstract and thus more flexible (Anderson, 1982; Glisky & Schacter, 1987; Schacter, 1985). This view is consistent with perceptual learning tasks (Hauptmann et al., 2005; Karni & Sagi, 1993) and motor sequence learning studies showing a decrease in transfer to untrained fingers (Korman et al., 2003; Tracy et al., 2001). Other learning theories suggest that both procedural and declarative knowledge may generalize during training (Allen & Brooks, 1991; Nokes & Ohlsson, 2005; Perkins & Salomon, 1987). These are supported by studies showing an increase in generalization during training in motor learning (Japikse, Negash, Howard, & Howard, 2003; Rand, Hikosaka, Miyachi, Lu, & Miyashita, 1998), mirror reading skill (Poldrack & Gabrieli, 2001), and phonological discrimination (Fenn et al., 2003) tasks. Generalization in procedural and declarative memory may depend on different parameters in the training experience. Declarative knowledge that is acquired through deliberate efforts to represent general principles at high level of abstraction, such as in mathematical problem solving, will therefore subsume a wider range of cases (Perkins & Salomon, 1987). However, procedural knowledge would also generalize broadly if the same skill is practiced in various contexts (Nokes & Ohlsson, 2005; Perkins & Salomon, 1987; Stokes, Lai, Holtz, Rigsbee, & Cherrick, 2008), for example, playing a variety of melodies when practicing an instrument would enhance generalization to untrained melodies.

In the current study, the increase in generalizability for the Letter-Alph group may arise from the procedural learning component. Because letter segmentation was trained in the varied context of different words, processes of segmentation and decoding become automatic and operate effortlessly on untrained stimuli. Alternatively, the declarative knowledge provided during direct letter instruction may be responsible for the enhanced generalizability because participants have learned an abstract segmentation rule that may be deliberately applied to new orthographies.

In conclusion, our results suggest that providing direct letter instruction prior to training on reading a new orthography results in reliance on different learning processes compared with individuals who receive only whole-word instruction. We suggest that the former relies more on a procedural learning mechanism, whereas the latter involves mainly declarative learning. This difference in the underlying learning mechanisms can explain the advantage found for direct letter instruction for reading acquisition in more natural settings. This study provides the first evidence that Offline improvement in performance, after the end of training, depends on the specific type of instruction and not only on the task at hand or sleep schedule.

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Supporting Information

Additional Supporting Information may be found in the online version of this article on Wiley Online Library:

Figure S1. The contribution of dummy variables coding for changes between sessions to a linear curve in the three groups. Red, the model; blue, Arcsine transformation of accuracy.