Journal of Experimental Psychology: Learning, Memory, and Cognition

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Online First Publication, September 19, 2011. doi: 10.1037/a0025646

Journal of Experimental Psychology:
Learning, Memory, and Cognition

0278-7393/11/$12.00 DOI: 10.1037/a0025646

RESEARCH REPORT

Implicit Word Learning Benefits From Semantic Richness: Electrophysiological and Behavioral Evidence

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Words differ considerably in the amount of associated semantic information. Despite the crucial role of meaning in language, it is still unclear whether and how this variability modulates language learning. Here, we provide initial evidence demonstrating that implicit learning in repetition priming is influenced by the amount of semantic features associated with a given word. Electroencephalographic recordings were obtained while participants performed a visual lexical decision task; the complete stimulus set was repeated once. Repetition priming effects on performance accuracy and the N400 component of the event-related brain potential were enhanced for words with many semantic features. These findings suggest a novel and important impact of the richness of semantic representations on learning and plasticity within the lexical-conceptual system; they are discussed in their relevance for assumptions concerning basic mechanisms underlying word learning.

Keywords: semantic features, implicit learning, repetition priming, visual word processing, ERPs

Language ultimately aims to convey meaning. Yet individual words differ widely in the amount of associated semantic information. Given the key role of meaning in language, the richness of semantic representations might be expected to drive language processing and language learning. Indeed, recent evidence suggests that semantic richness, as quantified, for example, by the number of associates generated in free-association tasks (Nelson, McEvoy, & Schreiber, 2004), the diversity of contexts in which a word appears (Adelman, Brown, & Quesada, 2006), or the number of associated semantic features as produced in feature-listing tasks (McRae, Cree, Seidenberg, & McNorgan, 2005), facilitates visual word processing in both semantic and nonsemantic tasks (Duñabeitia, Áviles, & Carreiras, 2008; Pexman, Hargreaves, Edwards, Henry, & Goodyear, 2007; Pexman, Holyk, & Monfils, 2003; Pexman, Lupker, & Hino, 2002). However, as yet it remains unclear whether and how the richness of semantic representations may influence language learning. In the present study, we explored this issue by investigating influences of the amount of associated semantic features on implicit word learning as reflected in repetition priming.

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This work was supported by a scholarship from the Berlin School of Mind and Brain to Milena Rabovsky and by German Research Foundation Grants AB 277/3 and 5 to Rasha Abdel Rahman. We would like to thank Melih Bakirtas for assisting in data acquisition and Daniel Schad for helping with the generalized linear mixed model analyses.

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Implicit learning occurs incidentally during information processing and is often assumed to be based on prediction errors. Specifically, it has been suggested that the brain incessantly and automatically anticipates upcoming events based on an experience-derived internal model of the environment. Deviations between anticipated and factual events are assumed to drive adaptations of internal representations to reduce future prediction errors and optimize processing (den Ouden, Friston, Daw, McIntosh, & Stephan, 2009; Friston, 2009; McClelland, 1994; McLaren, 1989; Schultz & Dickinson, 2000). Connectionist models of cognitive processes have implemented this assumption by learning rules that are based on error back-propagation (McClelland, 1994). Thus, the connection weight adjustments considered to underlie learning are proportional to the discrepancy between model-generated and correct output, representing predicted and factual information, respectively. Similarly, on a neural level, plasticity may be induced via prediction error signals altering synaptic efficacy (e.g., den Ouden et al., 2009; Friston, 2009).

A well-established measure of implicit learning is repetition priming, that is, the processing facilitation caused by the repeated encounter with a given stimulus (Schacter & Graf, 1986) that often goes along with reductions in brain activity (Henson, 2003). Priming effects are often considered to reflect an increase in the accessibility of the representations involved in processing the repeated stimulus (Graf & Mandler, 1984; Henson, 2003; Ratcliff, Hockley, & McKoon, 1985; Stark & McClelland, 2000; Wiggs & Martin, 1998). From the perspective of connectionism (Becker, Moscovitch, Behrmann, & Joordens, 1997; Stark & McClelland, 2000) or predictive coding (Friston, 2009), such increases in accessibility can be viewed as consequences of the continuous adaptation of the system aiming to reduce future prediction errors. Each encounter induces a refinement of the connections involved in processing the stimulus. These adaptations bring about the observed repetition-dependent performance benefit and reductions of cortical activity. It has also been suggested that repetition priming "reflects the very same connection adjustment process that gives rise to fluent reading ability" (Stark & McClelland, 2000, p. 965), further indicating repetition priming to provide a well-suited measure of the processes underlying implicit word learning.

Directly relevant to the question whether such learning may be modulated by semantic richness is the connectionist attractor model of lexical-conceptual processing proposed by Cree, McRae, and McNorgan (1999). This model relies on an error-based learning rule that is sensitive to the amount of semantic features associated with a given word and yields substantial positive correlations between the number of features and the computed error driving connection adaptations. Even though the model has primarily been used to account for performance in speeded lexical tasks at the endpoint of learning, it predicts enhanced adaptation, and thus enhanced implicit learning, for words with many semantic features.

In the present study, we investigated influences of the amount of associated semantic features on implicit word learning with a repetition priming design. Participants performed lexical decisions on visual words differing in the amount of semantic features according to the feature production norms of McRae et al. (2005; cf. Table 1 and the Appendix). These norms were obtained by asking participants to list semantic features (e.g., "is small," "can swim," etc.) for concrete words. The number of features listed for each word provides a measure of semantic richness, with participants listing more features for some words (e.g., 16 for *car*) than for others (e.g., seven for *cork*). The complete stimulus set was presented twice, and implicit learning was assessed by repetition priming effects on performance as well as event-related brain potentials (ERPs). Repetition priming has been consistently shown to reduce the amplitude of the N400 component, a negative-going ERP deflection at centro-parietal electrode sites with a maximum of about 400 ms (e.g., Doyle, Rugg, & Wales, 1996). The N400 has been related to semantic processing (Kutas & Federmeier, 2011) and—relevant for present purposes—also to the implicit prediction error assumed in connectionist models (McClelland, 1994). From this perspective, repetition-induced N400 amplitude reductions may reflect reduced error values for repeated stimuli due to connection adjustments triggered by the previous presentation. On the basis of the above-mentioned model of Cree et al. (1999), we predicted semantic richness to enhance adaptation.

Table 1
Stimulus Characteristics

Features	Many	Few
Number of features	16.1	9.3
Number of associates	13.6	13.6
Familiarity	6.3	6.1
Concreteness	6.1	6.0
Length (number of letters)	5.4	5.3
Word frequency	8.3	8.3
Number of orthographic neighbors	6.6	6.4
Number of phonological neighbors	14.4	14.4
Number of phonemes	4.4	4.3
Number of syllables	1.6	1.6

Specifically, repetition priming effects on performance and ERPs should be augmented for words associated with many as compared to few semantic features.

Method

Participants

Twenty-four native English speakers (12 women) with mean age of 25 years (range = 19–32) were paid €7 (~$10 U.S.) per hour for taking part in the study, after giving written informed consent. Participants had normal or corrected-to-normal visual acuity; 20 of them were right-handed.

Materials

Stimuli were 160 concrete English nouns (80 per semantic richness condition; cf. the Appendix) and 160 pseudowords. Within the word stimuli, the number of semantic features (McRae et al., 2005) varied across two levels (M = 16.1 vs. 9.3), while the number of associates, familiarity, concreteness, length, word frequency, and number of orthographic neighbors, phonological neighbors, phonemes, and syllables were controlled (all Fs < 1; please see Table 1). Most stimulus characteristics were taken from McRae et al. (2005). Number of associates and concreteness values were taken from Nelson et al. (2004). The word frequency values were retrieved from the English Lexicon Project (Balota et al., 2007) and represent log-transformed frequencies based on the HAL corpus (Lund & Burgess, 1996). CELEX-based frequency values were not intentionally matched between conditions, but post hoc comparison indicated that the difference was not statistically significant. Pseudowords were constructed by recombining the letters of the word stimuli (e.g., *osnop* from *spoon*). Pseudowords were pronounceable but orthographically less typical, as assessed by bigram frequencies and orthographic neighborhood size, Fs $(1, 318) > 9.2$, ps $< .01$ (Balota et al., 2007).

Procedure

Participants sat in a dimly lit, sound-attenuated, and electrically shielded chamber. Stimuli were presented in black on a light blue screen. Each trial began with a fixation cross, shown for 1.5 s, followed by a letter string, terminated with a response or when 3 s had elapsed. Immediately thereafter, the next trial started. Participants were instructed to indicate as fast and accurately as possible whether the letter string was a word or not by pressing one of two buttons with their left or right index finger. Response hand-to-stimulus assignments were counterbalanced. The complete stimulus set was presented twice, in two successive blocks. Each block was subdivided into two parts each consisting of 80 words (40 per semantic richness condition) and 80 pseudowords that were presented in a different random order for each participant and block. The order of the two parts was identical for the two successive blocks, counterbalanced across participants. Thus, the lag between subsequent presentations of the same word varied randomly between 160 and 480 intermediate words. Overall, the experiment comprised 640 trials, subdivided into 16 blocks of 40 trials each, separated by short breaks.

EEG Recording and Analysis

The electroencephalogram (EEG) was recorded with Ag/AgCl electrodes from 62 sites according to the extended 10-20 system and referenced to the left mastoid. Electrode impedance was kept below 5 kΩ. Bandpass of amplifiers (Brainamps) was 0.032–70 Hz; sampling rate was 500 Hz. Offline, the EEG was transformed to average reference, recommended as being less biased than other common references (Picton et al., 2000). Eyeblink artifacts were removed with a spatiotemporal dipole modeling procedure using BESA software. After applying a 30-Hz low-pass filter, the continuous EEG was segmented into epochs of 1 s, including a 200-ms prestimulus baseline. Trials with remaining artifacts or incorrect or missing responses were discarded.

ERP analyses focused on the N400 component, a negative ERP wave at centro-parietal sites peaking at about 400 ms. In accordance with the literature on ERP repetition effects (e.g., Doyle et al., 1996), we selected a cluster of centro-parietal sites (Cz, CP1, CPz, CP2, Pz) and analyzed mean amplitudes at these sites between 350 and 450 ms as well as between 450 and 550 ms. Amplitude values were submitted to repeated measures analyses of variance (ANOVAs) including the factors Features (many vs. few), Repetition (first vs. second presentation), and Electrode Site (Cz, CP1, CPz, CP2, Pz). In addition to subject-based (*F1*) analyses, we also conducted item-based (*F2*) ANOVAs, for which ERP amplitudes were averaged over subjects instead of over items (Hutzler et al., 2004).

Results

Performance

Because error rates (ERs) were very low, violating the ANOVA precondition of normal distribution, they were analyzed using logistic generalized linear mixed models, which do not entail such constraints and provide the additional advantage of allowing for simultaneous inclusion of both subjects and items as crossed random factors (Baayen, Davidson, & Bates, 2008; Schad, Nuthmann, & Engbert, 2010); response times (RTs) were analyzed accordingly.

Error rates. Analyses revealed no main effects of Features ($\beta = .33$, $SE = .24$, $p = .18$) or Repetition ($\beta = -.03$, $SE = .12$, $p = .80$). Importantly, we found the predicted interaction between Repetition and Features ($\beta = .55$, $SE = .23$, $p = .019$; please see Figure 1, bottom). ERs decreased with repetition for words with many features ($\beta = .30$, $SE = .16$, $p = .057$), while there was no repetition-induced facilitation for words with few features ($\beta = .24$, $SE = .17$, $p = .16$). Accordingly, while there was no effect of Features on accuracy during the first presentation ($\beta = .05$, $SE = .27$, $p = .84$), ERs were significantly lower for words with many as compared to words with few semantic features during the second presentation ($\beta = .60$, $SE = .27$, $p = .026$).

Response times. RTs did not differ between words with many versus few semantic features ($\beta = .006$, $SE = .015$, $t = 0.434$). Words were responded to faster during the second as compared to the first presentation ($\beta = .113$, $SE = .008$, $t =$

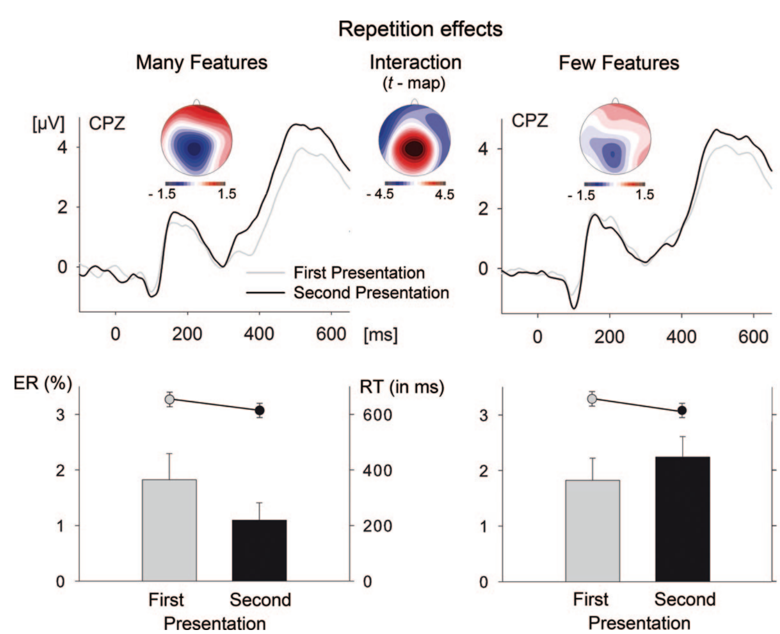

Figure 1. Repetition priming effects for words with many (left) versus few (right) semantic features. Top: Event-related potential waveforms at a centro-parietal electrode site (CPz) and topographical distribution of repetition effects (first minus second presentation) at peak (480 ms). The topography in the center depicts t values corresponding to the interaction between Repetition and Features (Repetition effects [first minus second presentation] for words with many vs. few semantic features); for $df = 23$, $p < .05$ if $t > 2.069$. Bottom: Error rates (ERs; bars) and response times (RTs; dots) for lexical decisions. Error bars depict standard errors of the mean.

13.977), and this effect was not modulated by the amount of semantic features ($\beta = -.012$, $SE = .016$, $t = -0.731$; see Figure 1, bottom).

Electrophysiology

ERP waveforms and topographies are depicted in Figure 1, top. The typical N400 repetition effect, with less negative amplitude for repeated stimuli, was well pronounced for words with many features but faint for words with few features. An ANOVA of mean ERP amplitudes between 350 and 450 ms revealed no main effect of Features ($F1 < 1$, $F2 < 1$). Repetition was not significant by subjects, $F1$ (1, 23) = 2.48, $p = .129$, but was significant by items, $F2$ (1, 158) = 14.27, $p <$ 001. Importantly, we again obtained the predicted interaction between Repetition and Features, $F1$ (1, 23) = 10.27, $p = .004$; $F2$ (1, 158) = 12.13, $p = .001$ (please see Figure 1 for a *t* map depicting the topographical distribution of the interaction), with a significant Repetition effect for words with many features, $F1$(1, 23) = 13.45, $p = .001$; $F2$ (1, 79) = 27.74, $p < .001$, but no such effect for words with few features ($F1 < 1$, $F2 < 1$). Accordingly, while amplitudes were significantly more negative for words with many features during the first presentation, $F1$ (1, 23) = 5.12, $p = .033$; $F2$ (1, 158) = 4.99, $p = .027$, there was a Features effect into the opposite direction for repeated stimuli, $F1$ (1, 23) = 6.77, $p = .016$; $F2$ (1, 158) = 6.12, $p = .014$.

In the segment between 450 and 550 ms, there was no main effect of Features, $F1$ (1, 23) = 1.31, $p = .264$; $F2 < 1$, but a significant main effect of Repetition, $F1$ (1, 23) = 6.31, $p = .019$; $F2$ (1, 158) = 36.98, $p < .001$. In this time window, the interaction between Repetition and Features was not significant by subjects, $F1$ (1, 23) = 2.29, $p = .144$, and only marginally significant by items, $F2$ (1, 158) = 3.04, $p = .083$. Following up this trend for an interaction in the item-based analysis revealed that even though Repetition modulated ERPs more strongly for words with many features than for words with few features (0.88 vs. 0.49 μV), Repetition effects were significant for both words with many, $F2$ (1, 79) = 30.35, $p < .001$, and words with few semantic features, $F2$ (1, 79) = 9.49, $p = .003$.

Discussion

The present study provides the first evidence that the richness of semantic representations modulates word learning. Specifically, we examined influences of the amount of semantic features associated with a given word on implicit visual word learning as assessed by repetition priming. We found enhanced repetition priming for words with many as compared to few semantic features in both lexical decision accuracy and ERPs. Thus, the richness of semantic representations advances repetition-induced changes in word processing considered to reflect implicit learning.

Even though the present study has focused on semantic influences on repetition priming, before discussing our findings in more detail we would like to note that we did not find effects of the number of features on performance during the first presentation of the stimuli as might have been expected based on previous evidence showing facilitated processing of words with richer semantic representations (e.g., Pexman et al., 2002). The absence of feature effects on performance during the first presentation may have been caused by task characteristics: Because words and pseudowords considerably differed in terms of orthographical typicality (e.g., bigram frequency), participants might have performed the lexical decision task based on low-level statistical regularities, processing the stimuli rather shallowly. Thus, the activation of semantic features may not have been necessary to solve the task, and there may not have been sufficient time to influence performance. Such an account is in line with previous evidence showing stronger influences of semantic features for more difficult tasks requiring longer processing or access to semantic representations (Pexman et al., 2002, 2003, 2007). Interestingly, in contrast to lexical decision performance when processing the stimuli for the first time, ERP modulations during the first presentation (see Amsel, 2011; Kounios et al., 2009; Müller, Duñabeitia, & Carreiras, 2010; Rabovsky, Sommer, & Abdel Rahman, 2011, in press, for related evidence) and, important for present purposes, the enhancement of repetition priming were observed despite the presumed shallow processing.

Why was an influence of semantic richness on repetition priming seen in ERs and ERPs but not in RTs? We suggest that factors other than the repetition of specific words also contributed to the RT decrease from the first to the second presentation. Such factors may be related to the progression of the task in general, such as increasing familiarity with the task and the environment, decision-related stimulus–response mappings, motor execution, and so on. This is indicated by analyses including the additional factor Presentation Order (first vs. second half of the stimulus set, within each presentation of the complete set): A highly significant effect of Presentation Order was found for RTs, $F(1, 23) = 8.83$, $p = .007$, but not for ERs ($F < 1$) or N400 amplitudes, $F(1, 23) = 1.70$, $p = .205$. As the stimulus set was subdivided into two parts for both the first and second blocks (with presentation order counterbalanced across participants; see the Method section, above), such effects of Presentation Order cannot be due to specific item characteristics. Thus, as the experiment progressed, processing speed was apparently enhanced not only by word repetition but also by a number of factors unrelated to the repetition of specific words and hence also unrelated to the number of features of these words. Repetition effects on ERs and N400 amplitudes, on the other hand, were seemingly less influenced by these unspecific factors and more strongly influenced by the repetition of specific words. This might have made these measures more sensitive to influences of the richness of semantic representations on repetition priming.

There are alternative views of the mechanisms underlying repetition priming (Henson, 2003). It is often assumed that repetition facilitates processing by increasing the accessibility of the representations involved in processing the repeated stimuli (Graf & Mandler, 1984; Ratcliff et al., 1985; Stark & McClelland, 2000; Wiggs & Martin, 1998), and we would like to suggest that semantic richness enhances this repetition-induced increase in accessibility. Importantly, however, repetition effects may also be due to the formation of a more direct link between stimuli and responses (Dobbins, Schnyder, Verfaellie, & Schacter, 2004). Such a link can allow for bypassing or curtailing processing stages involved in initial processing. Critically, in the frame of this direct link account, it might be assumed that the obtained influences of semantic richness on N400 repetition effects reflect a differential repetition-induced reduction of semantic involvement. Specifically, upon initial presentation, enhanced N400 amplitudes for words with many features might indicate semantic involvement, whereas semantic involvement—and hence N400 amplitudes—might be close to floor level for words with few features. During repetitions, when responses are faster, semantic involvement might be reduced for words with many features; in contrast, N400 amplitudes to words with few features might be already near floor during initial presentations and therefore not be much further diminished by repetition.

However, it does not seem that there was a floor issue for words with few semantic features during the first presentation because, during the second presentation, words with many features elicited even smaller N400 amplitudes than words with few features. It does not seem plausible that during repetition, words with many semantic features would entail less semantic involvement than words with few semantic features. Furthermore, the plausibility of attributing the differential repetition effect to a floor issue with the few feature stimuli is called into question also by the finding that ERs for both kinds of words did not differ during the first presentation, the interaction between repetition and features being obtained nonetheless. Thus, influences of semantic richness on repetition priming seem to reflect semantic influences on repetition-induced increases in accessibility (Graf & Mandler, 1984; Ratcliff et al., 1985; Stark & McClelland, 2000; Wiggs & Martin, 1998) rather than differential curtailing of semantic involvement due to rapid response learning (Dobbins et al, 2004).

It is also important to note that while repetition priming was enhanced for words with many features, it was present for words with few features as well. First, even though ERs did not decrease with repetition for words with few semantic features, repetition enhanced response speed for all words in equal measure with a benefit of 42 ms for words with few and 39 ms for words with many features. As this considerable RT decrease was accompanied by constant ERs (speaking against the possibility of a speed–accuracy tradeoff), it indicates a genuine repetition benefit in performance for words with few features as well (even though, of course, diminished as compared to the combination of a decrease in both RTs and ERs for words with many features). Similarly, in the ERP data, we observed repetition effects for words with few features as well, even though attenuated as compared to the well-pronounced ERP repetition effects for words with many features. Thus, both performance and ERP data are in line with the notion that repetition priming is enhanced for words with many features but occurs for words with few features as well.

As noted in the introduction, such influences of semantic richness on repetition priming are directly predicted by the connectionist attractor model of lexical-conceptual processing proposed by Cree et al. (1999). This model relies on an error back-propagation learning rule that is sensitive to semantic richness; the number of semantic features associated with a given word is positively correlated with the overall error used as a basis for connection adaptations. Although the model has not yet been applied to semantic influences on learning and plasticity, it predicts enhanced connection adjustments and hence enhanced implicit learning for words with many semantic features.

The observed influences of semantic richness seem to be particularly telling in relation to a study by Stark and McClelland (2000), which raised issues concerning the basic mechanisms underlying word learning. The authors found larger repetition priming effects for words than for nonwords and took their findings to challenge most connectionist reading models, namely, those relying on error-driven learning. In these models, less trained stimuli, such as nonwords, should produce larger error values, which should result in enhanced adaptation and thus enhanced implicit learning. However, the present results suggest that the predicted enhancement of nonword learning due to the sparseness of prior training may have been offset by an opposing mechanism, namely, the enhancement of learning of meaningful words relative to nonwords, due to the obviously much richer semantic representations of the former. Crucially, as influences of semantic richness on implicit learning are in line with an error-based model of lexical-conceptual processing (Cree et al., 1999), they may resolve the apparent contradiction between the priming results found by Stark and McClelland and error-based models of reading.

It remains to be explored how far the reported driving influence of semantic richness on implicit visual word learning generalizes to other perceptual modalities (e.g., visual vs. auditory) and domains (e.g., language vs. object recognition). Given the crucial role of meaning in guiding human behavior, driving influences of semantic richness on learning may go beyond visual word learning. However, further research is required to examine this suggestion. The present results seem to mark a promising first step and should be taken into account when aiming to understand and describe reading development (Seidenberg & McClelland, 1989).

It is important to note, however, that we do not want to make statements concerning the learning of new words, that is, adding new representations to memory. Our focus is on investigating a learning process that presumably involves the update of internal models of probabilities of occurrence of the encountered (previously known) words. Within the frame of the complementary systems approach to learning and memory (Davis & Gaskell, 2009; McClelland, McNaughton, & O'Reilly, 1995), the investigated learning process presumably does not correspond to the fast acquisition of new associations and specific episodes as supported by the hippocampus; instead, we suggest that it relates to the slow cortical learning induced by the slight adaptation of the cortical synapses that are directly involved in processing the corresponding stimulus. Such subtle adaptations of cortical connections presumably take place for all stimuli, which are processed by the system, including previously unknown words (Stark & McClelland, 2000); for unknown words, however, they are supposedly not sufficient for building stable representations.

In this context, we would also like to note that there is debate concerning the subdivision of memory into distinct systems and specifically which variable should be regarded as critical in distinguishing between the presumed systems (e.g., consciousness, intention, binding, new associations; see, e.g., Reder, Park, & Kieffaber, 2009, for review). The present study does not intend to contribute to this debate. Rather, we discuss our findings as an instance of implicit learning (and slow cortical instead of fast hippocampus-driven learning), based on using repetition priming during lexical decisions as a typical implicit memory task, with no information about subsequent repetitions given during initial exposure, and the speeded lexical decision task offering little incentive and time for intentional recollection upon repetition. Regarding our findings as an instance of implicit learning is also consistent with a study by Schott, Richardson-Klavehn, Heinze, and Düzel (2002) aiming to disentangle ERP correlates of implicit versus explicit memory encoding, which found that enhanced N400 amplitudes during initial exposure predicted priming but not explicit memory during subsequent presentation, nicely fitting with our finding of larger N400 amplitudes for those words for which implicit learning was enhanced.

In conclusion, the enhancement of repetition priming for words with many semantic features seems to reveal a natural account of the evolvement of semantic richness benefits in visual word processing over time (Duñabeitia et al., 2008; Pexman et al., 2002, 2003, 2007). If the amount of semantic features associated with a given word enhances learning during every single encounter, repeated presentations should naturally entail the observed benefit. In a nutshell, semantically rich words benefit more from each encounter, as expressed in the biblical parable of the talents: “For to everyone who has, more shall be given, and he will have an abundance” (Matthew 25:29, New American Standard Bible).

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Appendix

Stimuli: Words With Few Features, Words With Many Features, and Pseudowords

Few features	Pseudowords	Many features	Pseudowords
ball	lalb	balloon	olanolb
barrel	reralb	barn	ranb
basket	kasteb	basement	estenamb
belt	telb	boots	ostbo
biscuit	cistibu	bra	rab
boat	atob	bread	ardeb
bucket	cebtuk	cabbage	becagab
buckle	celbuk	cake	ecka
bull	lulb	cannon	nocnan
cabinet	nebaict	canoe	ocena
cape	acep	carpet	trepac
cathedral	daltacher	carrot	tracor
cellar	lacrel	cat	tac
chapel	hecalp	cheese	esehec
cherry	hyrcer	coat	acot
chisel	helcis	couch	hucco
clam	almc	cougar	uragoc
clamp	plamc	cow	cwo
cloak	ackol	crown	wrocn
coin	ocni	cucumber	mucrebuc
cork	ockr	cup	ucp
crow	wroc	deer	edre
dish	hisd	desk	ksed
dove	odev	dog	ogd
drill	rilld	eagle	lagee
emerald	medreal	elephant	hetapnel
envelope	olpeneve	duck	uckd
fence	enfec	fawn	wanf
gown	nowg	flea	elfa
guitar	igartu	football	olfolbta
harp	phra	frog	gorf
hawk	whak	garlic	ilgrac
helmet	ethlem	gate	egta
hook	okho	goat	otga
hornet	nethor	grape	repga
hut	thu	hammer	mehram
inn	nin	hare	erha
mirror	orrirm	house	sueho
nightgown	thnongwig	lobster	trelbos

(*Appendix continues*)

Appendix (*continued*)

Few features	Pseudowords	Many features	Pseudowords
oak	koa	marble	rembla
owl	wlo	missile	imselis
pajamas	japsaam	napkin	knapni
pepper	prepep	necklace	canklece
pie	ipe	olive	eivlo
pier	erip	peach	cepha
pin	inp	pen	enp
pine	ipen	pencil	nelpic
porcupine	nirpocupe	penguin	inupneg
pumpkin	minkupp	pickle	cepilk
raccoon	norcaco	pig	ipg
raspberry	persybrar	pistol	spiotl
rattle	telart	pony	nyop
razor	orraz	potato	ottopa
rice	cire	radio	aidor
rock	crok	rake	eark
rocket	certok	rat	tra
sack	kacs	robe	breo
salmon	lomnsa	robin	brino
scarf	crafs	rooster	orserot
shell	lelsh	ruler	erurl
shield	ledsih	sandals	nassald
slippers	spespirl	screwdriver	werdirsverc
snail	alins	seagull	ugalels
spade	peads	sheep	hespe
spatula	lastaup	shirt	thris
stick	scikt	shoes	hesos
stone	tseon	sink	nisk
table	belat	sofa	foas
taxi	aixt	spider	drepis
tent	tetn	spoon	osnop
toilet	ilotte	squirrel	resluriq
tomato	mootat	sword	wrods
toy	yto	tangerine	garneetin
truck	kurct	tiger	griet
umbrella	marblule	toad	odat
vest	tves	trousers	restusor
vine	eniv	turtle	rettlu
walnut	luntaw	typewriter	priwetret
whale	helwa	wasp	psaw
worm	rowm	whistle	shelwit

Received February 11, 2011
Revision received August 8, 2011
Accepted August 12, 2011 ■