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BRIEF REPORT

The influence of emotion on lexical processing: Insights from RT distributional analysis

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Abstract In two lexical decision experiments, the present study was designed to examine emotional valence effects on visual lexical decision (standard and go/no-go) performance, using traditional analyses of means and distributional analyses of response times. Consistent with an earlier study by Kousta, Vinson, and Vigliocco (Cognition 112:473–481, 2009), we found that emotional words (both negative and positive) were responded to faster than neutral words. Finer-grained distributional analyses further revealed that the facilitation afforded by valence was reflected by a combination of distributional shifting and an increase in the slow tail of the distribution. This suggests that emotional valence effects in lexical decision are unlikely to be entirely mediated by early, preconscious processes, which are associated with pure distributional shifting. Instead, our results suggest a dissociation between early preconscious processes and a later, more task-specific effect that is driven by feedback from semantically rich representations.

Keywords Visual word recognition · Response time distributional analyses · Emotional valence · Emotion · Semantics · Semantic richness · Lexical decision

In recent years, increasing interest has focused on the reciprocal interactions between emotional and cognitive processing (Okon-Singer, Lichtenstein-Vidne, & Cohen, 2013). Toward this end, various paradigms have been developed that employ linguistic stimuli to explore the processing differences between positive (e.g., JOY), negative (e.g., SIN), and neutral (e.g., SUM) words. For example, in the emotional Stroop task, participants name the colors of emotional and neutral words, whereas in the lexical decision task (LDT), participants have to discriminate between real words and made-up words (e.g., FLIRP). Earlier work had suggested slower responses to emotional than to neutral words (Algom, Chajut, & Lev, 2004), as well as slower responses to negative than to positive words (Estes & Adelman, 2008). The slowing associated with negative stimuli is consistent with the *automatic-vigilance* perspective (Wentura, Rothermund, & Bak, 2000), which claims that emotional stimuli attract attention in early processing. Since it takes more time to disengage attention from emotional stimuli, they interfere with and slow down the processes underlying color naming and lexical decision.

However, the work described above is qualified by an important methodological limitation. Specifically, in a meta-analysis of 32 published emotional Stroop studies, Larsen, Mercer, and Balota (2006) reported that, as compared to neutral words, emotional words had more letters, were lower in frequency, and had fewer orthographic neighbors. Hence, the well-documented slowing associated with emotional words may partly reflect a failure to control for correlated lexical characteristics. In this light, more recent studies investigating emotional valence effects have used carefully controlled linguistic stimuli. For example, Kousta, Vinson, and Vigliocco (2009) compared lexical decision latencies to positive, neutral, and negative words, after matching these words on many lexical characteristics. Surprisingly, they reported that emotional words (both positive and negative) were responded to *faster* than neutral words (see also Syssau & Laxen, 2012; Vinson, Argyriou, Cuadrado, & Vigliocco, 2011).

Kousta et al. (2009) suggested that their processing advantage for emotional words was consistent with the model of motivated attention and affective states (Lang, Bradley, & Cuthbert, 1990), which assumes that emotions are fundamentally organized around two motivational systems, defensive and appetitive. The former is activated in response to threats (i.e., negative stimuli), whereas the latter is activated in

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contexts that promote survival (i.e., positive stimuli). Hence, attention is captured and sustained by motivationally relevant negative and positive stimuli, relative to neutral stimuli. Kousta et al. also speculated that such enhanced perceptual processing for emotional stimuli most likely reflected early preconscious processes (Gaillard et al., 2006; Zeelenberg, Wagenmakers, & Rotteveel, 2006), although *how* such processes facilitate word recognition remains unclear.

However, facilitatory emotional valence effects in lexical decision performance can be accommodated by an alternative theoretical perspective. Considerable empirical evidence (see Pexman, 2012, for a review) has indicated that *semantic richness*, a multidimensional construct reflecting the extent of variability in the information associated with a word's meaning, facilitates visual word recognition (Pexman, Hargreaves, Siakaluk, Bodner, & Pope, 2008). Semantic richness encompasses dimensions such as imageability, number of semantic features, number of associates, proximity of semantic neighbors, body–object interaction, number of senses, and emotional valence. According to this perspective, positive and negative words are associated with relatively more semantic information than neutral words, and hence elicit more semantic feedback activation to the word level.

Importantly, the two perspectives cannot be distinguished at the level of mean response times (RTs). Specifically, because mean differences may result from distributional shifting, an increase in the slow tail of the distribution, or some combination of both, mean-level analyses may not be sensitive to more subtle aspects of performance. In the present study, we carried out RT distributional analyses to quantify the influences of variables on different portions of the RT distribution (Balota & Yap, 2011). The first approach involved fitting empirical RT distributions to the theoretical ex-Gaussian function, a convolution of the normal and exponential distributions. This yields three parameter estimates: μ (mean of normal distribution), σ (standard deviation of normal distribution), and τ (mean and standard deviation of exponential component). Distributional shifts are reflected by μ changes, whereas changes in the distributional tail are reflected by τ changes. Additionally, because the mean RT is the algebraic sum of μ and τ, mean differences can be partitioned into distributional shifting (μ) and modulations in the tail of the distribution (τ). We also generated quantile plots, which provide a graphical, nonparametric complement to ex-Gaussian analyses. Specifically, RTs for each participant are rank-ordered (from fastest to slowest) as a function of condition, and the quantiles (e.g., .1, .2, .3, . . .) for each condition are plotted. Experimental effects that are mediated by shifting (μ) are reflected by a flat line, whereas effects that are mediated by the tail increase in magnitude across the RT distribution.

To recapitulate, it is unclear whether emotional valence effects in lexical decision are accommodated better by early, preconscious processes or by semantic feedback during the word recognition process. RT distributional analyses can help tease these alternatives apart. As we mentioned, the manner in which early, preconscious processes facilitate the perceptual processing of emotional words has not been well-specified. However, work from the priming literature might provide some constraints here. For example, masked repetition priming effects (Gomez, Perea, & Ratcliff, in press) and masked semantic priming effects for skilled readers (Balota, Yap, Cortese, & Watson, 2008) are reflected by pure distributional shifting, consistent with the idea that masked identity primes and semantically related primes speed up target processing through an early and relatively modular head-start mechanism. The emotional content of words could capture attention and preactivate lexical representations in the same prospective manner. This prediction is captured by RT distributional shifting, wherein the magnitude of emotional valence effects is similar across the RT distribution.

On the other hand, if valence effects are driven by top-down activation from semantic-level to word-level representations, valence should shift *and* increase the tail of the RT distribution, much like word frequency. Specifically, emotional words, as compared to neutral words, should be associated with both a faster leading edge (μ) and a lighter distributional tail (τ). According to this perspective, semantic feedback should facilitate early lexical processing (indexed by a faster leading edge), while reducing later, attention-demanding postlexical checking (indexed by a lighter tail) (Balota & Spieler, 1999).

Interestingly, although word frequency and semantic priming effects have been well-studied with RT distributional analyses (see Balota & Yap, 2011, for a review), to our knowledge, the effects of semantic richness (e.g., imageability, emotional valence, number of features) have not yet been investigated in this manner. Hence, the present study, in addition to providing interesting new constraints on the locus of emotional valence effects in lexical decision, will also shed light on how a particular semantic-richness dimension (i.e., emotional valence) influences underlying RT distributions.

Method

Experiment 1 (E1) was a literal replication of Kousta et al. (2009), using identical word stimuli. In Experiment 2 (E2), we evaluated the robustness and generalizability of E1's results, using the go/no-go lexical decision paradigm (Perea, Rosa, & Gómez, 2002). The go/no-go task does not require an overt response for nonwords, thereby simplifying response selection by minimizing response competition (Gordon, 1983). Indeed, this is consistent with empirical evidence that the go/no-go LDT, as compared to the standard word/nonword task, yields faster and more accurate responses, while imposing fewer task-specific demands on processing resources (Perea et al., 2002).

Participants

A total of 96 undergraduates from the National University of Singapore (NUS) participated in the study for course credit (E1: 44, E2: 52). The participants' first language was English, and they had normal or corrected-to-normal vision. The participants from the two experiments were not significantly different on Shipley (1940) vocabulary scores ($t < 1$).

Design

A single-factor within-subjects design was used: valence (negative, neutral, positive). The dependent variables were RTs and accuracy rates.

Stimuli

The stimuli consisted of the 120 words[1] used by Kousta et al. (2009), which carefully matched negative, neutral, and positive words on concreteness, imageability, age of acquisition, familiarity, word frequency, orthographic neighborhood density, length (letter, syllabic, morphemic), and mean position bigram frequency. Nonword distractors were created with Wuggy, which generates nonwords that are matched to word targets on subsyllabic structure and transition frequencies (Keuleers & Brysbaert, 2010).

Procedure

Participants were individually tested in sound-attenuated cubicles and were seated about 60 cm away from the screen. PC-compatible computers running E-Prime software (Schneider, Eschman, & Zuccolotto, 2001) were used for stimulus presentation and data collection. All stimuli were presented in white uppercase 18-point Courier New font and centered on a black background. After completing a computer-based vocabulary task (Shipley, 1940), participants were instructed to silently read each letter string that was presented and to decide whether each letter string formed a word or nonword. For E1 (standard LDT), participants pressed the *slash* ("/") key for words and the "z" key for nonwords. For E2 (go/no-go LDT), they pressed the same key for words but were instructed to withhold their responses for nonwords. Participants were told to respond as quickly and accurately as possible.

Each experiment began with 20 practice trials, followed by 240 experimental trials whose order was randomized anew for each participant. Breaks occurred after every 60 trials. Each trial consisted of the following sequence of events: (a) a fixation point (+) in the middle of the screen for 400 ms, (b) a blank screen for 250 ms, and (c) the stimulus presented at the position of the fixation point for 2,500 ms. After an incorrect response, a 170-ms tone and a message stating that the response was incorrect was presented slightly below the fixation point for 1,000 ms, after which the screen was cleared.

Results

For both experiments, errors and RTs faster than 200 ms or 2.5 *SD*s above or below each participant's mean RT were removed.[2] Repeated measures analyses of variance by participants and items were then carried out on the mean RTs and accuracies, and by participants for the ex-Gaussian parameters (μ, σ, τ), which were obtained using the quantile maximum likelihood estimation (QMLE) procedure in the QMPE program (Version 2.18; Cousineau, Brown, & Heathcote, 2004). QMLE provides unbiased parameter estimates and has been shown to be an effective method for small samples (Heathcote & Brown, 2004). All fits converged successfully within 250 iterations. The descriptive statistics for mean RTs, accuracy rates, and ex-Gaussian analyses for both experiments are presented in Table 1.

Experiment 1

RT and accuracy Data-trimming procedures removed 7.6 % (5.1 % errors, 2.5 % RT outliers) of the trials. For mean RTs, the effect of valence was significant by both participants and items [$F_p(2, 86) = 28.60$, $MSE = 306$, $p < .001$, $\eta_p^2 = .399$; $F_i(2, 117) = 6.43$, $MSE = 2{,}021$, $p = .002$, $\eta_p^2 = .099$]. Turning to the accuracy analyses, the effect of valence was also significant by both participants and items [$F_p(2, 86) = 50.09$, $MSE = .001$, $p < .001$, $\eta_p^2 = .538$; $F_i(2, 117) = 5.16$, $MSE = .008$, $p = .007$, $\eta_p^2 = .081$]. Post hoc tests indicated that, as compared to neutral words, negative and positive words were reliably faster and more accurate, with no significant difference in RTs and accuracy rates between positive and negative words.

[1] Kousta et al. (2009) excluded two triplets containing RABBI and ETHER in their analyses, because these two items were associated with low accuracy rates. Our analyses yielded the same broad pattern of results with and without these triplets.

[2] These cleaning criteria have generally been adopted in other studies that have featured RT distributional analyses (see Balota & Yap, 2011, for a review). However, we also analyzed the data with other thresholds (i.e., removing RTs more than 3 *SD*s away or removing only errors and RTs faster than 200 ms). Importantly, the observed effects did not change, at both the level of the means and the level of RT distributional characteristics.

Table 1 Mean response times (RTs), accuracy, and ex-Gaussian parameters as a function of experiment and valence

	RT	Accuracy	μ	σ	τ
Experiment 1 (LDT)					
Neutral words	571 (70)	.911 (.052)	467 (41)	46 (18)	104 (47)
Negative words	545 (66)	.967 (.032)	454 (48)	41 (15)	93 (32)
Positive words	547 (68)	.968 (.034)	456 (49)	44 (16)	93 (43)
Negative valence effect	*26*	*.056*	*13*	*5*	*11*
Positive valence effect	*24*	*.057*	*11*	*2*	*11*
Experiment 2 (Go/No-go)					
Neutral words	530 (48)	.968 (.039)	446 (35)	50 (20)	85 (39)
Negative words	502 (46)	.996 (.010)	431 (33)	41 (14)	72 (32)
Positive words	502 (44)	.997 (.009)	434 (36)	45 (17)	69 (34)
Negative valence effect	*28*	*.028*	*15*	*9*	*13*
Positive valence effect	*28*	*.029*	*12*	*5*	*16*

Standard deviations are presented in parentheses

Ex-Gaussian parameters For μ, the main effect of valence was significant [$F(2, 86) = 4.68$, $MSE = 508$, $p = .012$, $\eta_p^2 = .098$]: μ was larger for neutral than for emotion words, and no difference emerged between positive and negative words. Turning to σ, we found no effect of valence, $F < 1$. Finally, for τ, the main effect of valence approached significance [$F(2, 86) = 2.67$, $MSE = 745$, $p = .075$, $\eta_p^2 = .058$]. Critically, post hoc tests indicated borderline-reliable differences between neutral and negative words ($p = .05$) and between neutral and positive words ($p = .06$), but no difference between positive and negative words.

Experiment 2

RT and accuracy Data-trimming procedures removed 5.0 % (3.5 % errors, 1.5 % RT outliers) of the trials. For mean RTs, the effect of valence was significant by both participants and items [$F_p(2, 102) = 76.00$, $MSE = 171.28$, $p < .001$, $\eta_p^2 = .598$; $F_i(2, 117) = 7.02$, $MSE = 1{,}983$, $p = .001$, $\eta_p^2 = .107$]. Turning to the accuracy analyses, the effect of valence was also significant by both participants and items [$F_p(2, 102) = 31.36$, $MSE = .0005$, $p < .001$, $\eta_p^2 = .381$; $F_i(2, 117) = 3.74$, $MSE = .003$, $p = .027$, $\eta_p^2 = .060$]. Post hoc tests indicated that, as compared to neutral words, negative and positive words were reliably faster and more accurate, with no significant difference in RTs and accuracy rates between positive and negative words.

Ex-Gaussian parameters For μ, the main effect of valence was significant [$F(2, 102) = 9.64$, $MSE = 352$, $p < .001$, $\eta_p^2 = .159$]; the parameter was larger for neutral than for emotion words, with no μ difference between positive and negative words. Turning to σ, we observed a main effect of valence [$F(2, 102) = 5.46$, $MSE = 191$, $p = .006$, $\eta_p^2 = .097$]; post hoc tests revealed that this effect was entirely due to σ being larger for neutral than for negative words ($p = .002$). Finally, for τ, the main effect of valence was significant [$F(2, 102) = 6.62$, $MSE = 601$, $p = .002$, $\eta_p^2 = .115$]. Critically, post hoc tests indicated reliable differences between neutral and negative words ($p = .005$) and between neutral and positive words ($p = .003$), but no difference between positive and negative words.

Summary of results

Consistent with Kousta et al. (2009), the participants in both experiments responded faster to both negative and positive words than to neutral words; we observed no difference between positive and negative words at the level of mean RTs. Intriguingly, the distributional analyses also revealed similar distributional signatures for positive and negative valence effects in both experiments. Specifically, valence effects (positive and negative) were reflected by both μ and τ (see Table 1). For example, the negative valence effect in E1 was 26 ms, which was mediated by changes of approximately similar magnitude in μ (13 ms) and τ (11 ms). That is, both positive and negative valence effects were reflected by a combination of distributional shifting and an increase in the tail of the distribution.

To illustrate these effects visually, we also plotted the mean quantiles (.1, .3, .5, .7, and .9) for the different experimental conditions (see Figs. 1 and 2); theoretical quantiles were estimated using Monte Carlo simulations. In the top two panels of each figure, the empirical quantiles are represented by data points and standard error bars, while the estimated quantiles for the best-fitting ex-Gaussian distribution are

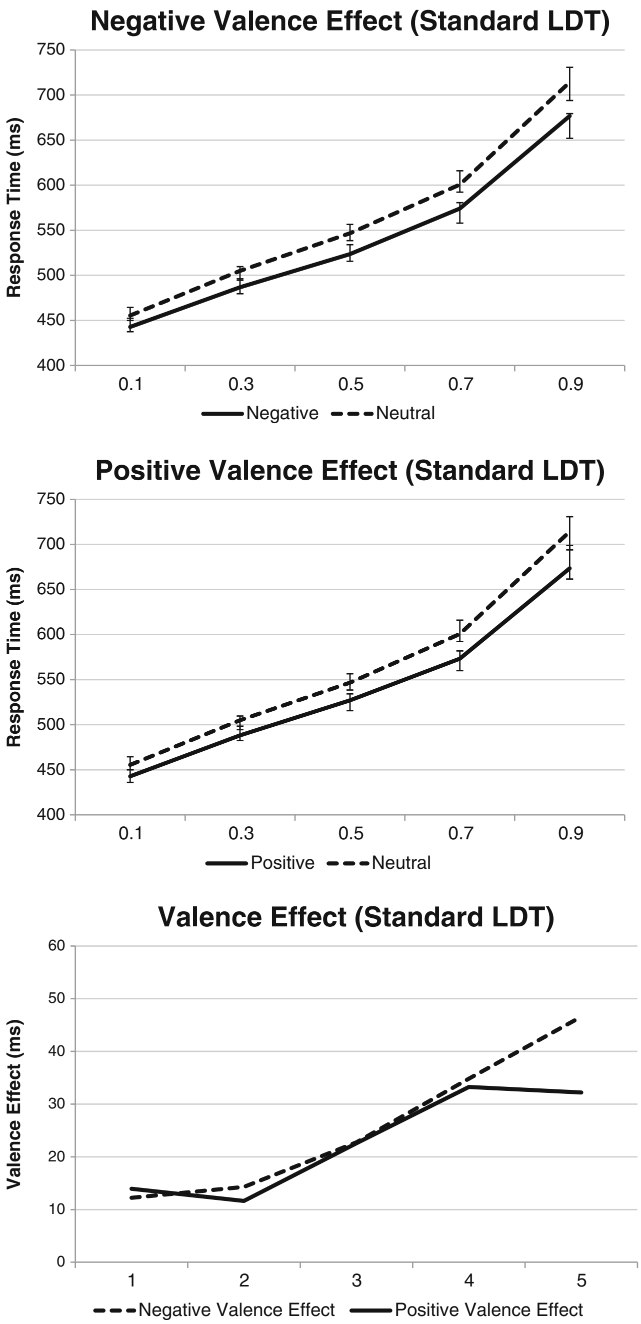

Fig. 1 Lexical decision performance from Experiment 1 (standard lexical decision task [LDT]) as a function of valence and quantiles for negative (top panel) and positive (middle panel) words. Empirical quantiles are represented by error bars, whereas fitted ex-Gaussian quantiles are represented by lines. The bottom panel shows valence effects as a function of valence. RT = response time

represented by lines. The bottom panel of each figure represents valence effects as a function of valence. In general, we found good overlap between the empirical and theoretical quantiles (within one standard error for all quantiles), indicating that the empirical data were well-captured by the ex-Gaussian parameters. The plots can be summarized simply: Valence effects were smallest for the fastest trials, and increased sharply across the RT distribution for both positive and negative words. Importantly, distributional signatures for positive and negative valence effects were similar, consistent with the ex-Gaussian analyses.

Discussion

In the present study, we explored the effects of positive and negative emotion on lexical decision, using both the standard and go/no-go LDTs. In both tasks, we replicated the intriguing pattern reported by Kousta et al. (2009), wherein emotion words, regardless of polarity, were responded to faster than carefully matched neutral words. RT distributional analyses also revealed that positive and negative valence effects were mediated to the same extents by distributional shifting and by an increase in the tail of the distribution. Across the distribution, valence effects sharply increased as RTs became longer. These effects were robust; the same mean-level and distributional-level effects were observed in two different LDT paradigms. We now consider the theoretical implications of these findings.

Are emotional valence effects in lexical decision driven entirely by early, preconscious processes?

An important goal of the present study was to understand better the mechanisms underlying the facilitatory influence of emotional words in lexical decision. Specifically, are early preconscious processes *solely* responsible for these effects, as is suggested by the model of motivated attention and affective states (Lang et al., 1990)? In general, our results are inconsistent with this view. Specifically, facilitated perceptual processing for emotional stimuli is unlikely to be driven *entirely* by early, preconscious processes. Instead, the influence of emotional valence more closely resembles the effect of word frequency, wherein faster latencies for positive and negative words implicate both the facilitation of early, lexical processes (faster leading edge) and the reduction of late, attention-demanding, decision-based mechanisms (lighter tail) (see Balota & Spieler, 1999).

Interplay between emotional valence and task-specific mechanisms

To recapitulate, our results unequivocally demonstrate that facilitated processing for emotional words in lexical decision are largely attributable to modulations in the tail of the distribution. In addition to earlier processes, emotional valence effects in lexical decision also appear to implicate attentionally demanding task-specific word/nonword discrimination processes. Compatible with this, the two-stage model of lexical decision (Balota & Spieler, 1999) proposes that stimuli that

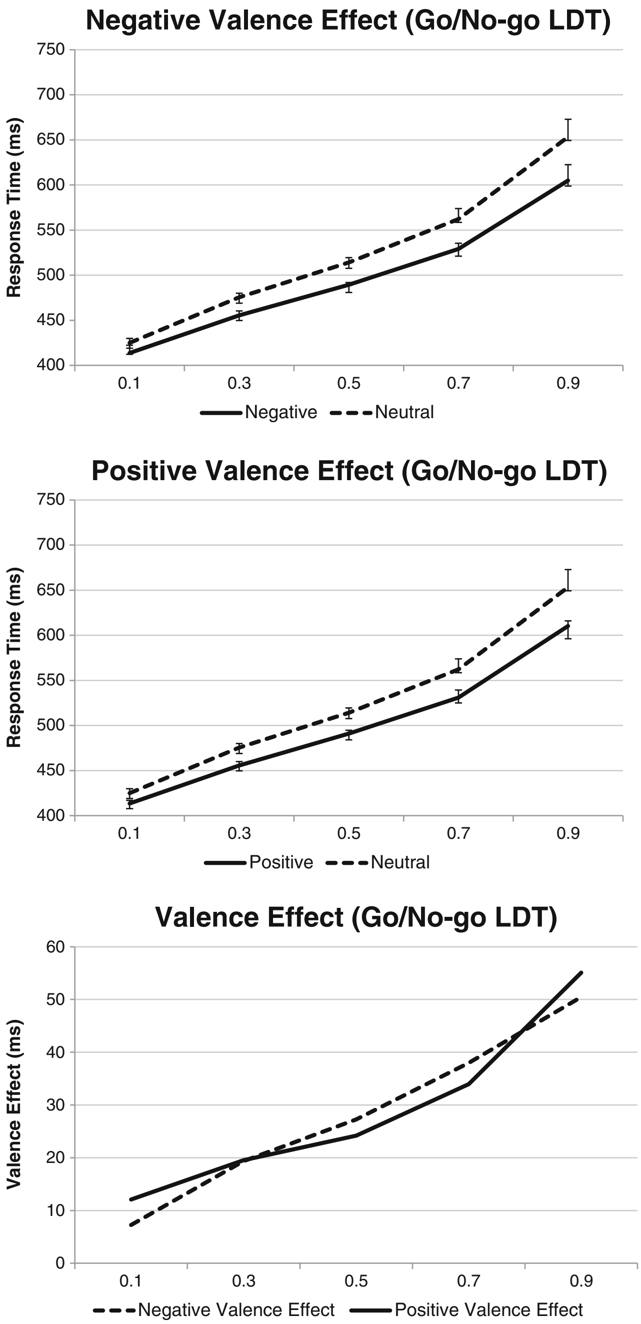

Fig. 2 Lexical decision performance from Experiment 2 (go/no-go lexical decision task [LDT]) as a function of valence and quantiles for negative (top panel) and positive (middle panel) words. Empirical quantiles are represented by error bars, whereas fitted ex-Gaussian quantiles are represented by lines. The bottom panel shows valence effects as a function of valence. RT = response time

are high (high-frequency words) or low (orthographically illegal nonwords) in familiarity/meaningfulness (FM) can be responded to rapidly, but stimuli with intermediate FM values (low-frequency words) are more likely to engage slower, attentionally demanding checking processes. Within this framework, emotional words should be more familiar/meaningful than neutral words, because they are associated with richer semantic representations that provide stronger feedback to word-level representations (Pexman, 2012), thereby reducing the amount of attention required to respond to such words. In principle, our findings can also be accommodated by the single-process diffusion model of lexical decision (Ratcliff, Gomez, & McKoon, 2004), which claims that lexical decisions are based on the accumulation of noisy information over time. Emotional words could be associated with a steeper drift rate (i.e., rate of information accrual), which yields a faster leading edge and lighter distributional tail.

Although our results can be explained by the semantic-richness account, which makes no special distinction between emotional valence and other semantic dimensions, it is important to point out that these findings are also compatible with newer embodied perspectives that allow a much more prominent role for emotion. For example, Kousta, Vigliocco, Vinson, Andrews, and Del Campo (2011) argued that the representation and processing of abstract semantics is grounded in experiential information comprising sensorimotor information and emotion.

Dissociating early and late effects of emotional valence

Although we have suggested that emotional valence effects in lexical decision tap relatively late controlled processes, we are of course not arguing for a late locus across *all* tasks. Such a view would be inconsistent with studies indicating that participants are sensitive to valence information even in the absence of conscious awareness (e.g., Gaillard et al., 2006). For example, Nasrallah, Carmel, and Lavie (2009) reported that when participants had to classify subliminally presented words as emotional or neutral, classification accuracy was reliably higher for negative than for positive words. Similarly, in a forced choice perceptual identification task, participants correctly identified masked emotional words more accurately than masked neutral words (Zeelenberg et al., 2006). Event-related potential (ERP) studies that have examined the time course of emotional valence effects are also consistent with the view that negative emotional content is processed very early (Scott, O'Donnell, Leuthold, & Sereno, 2009). However, although the foregoing review is consistent with the view that perceptual sensitivity to emotionally significant words can be both early and preconscious, it is worth noting that the studies described above are mostly based on data-limited paradigms in which participants responded to briefly presented masked stimuli that could not be consciously identified.

In the present study, like Kousta et al. (2009), we used fully visible lexical targets whose identities participants did not have to "guess." Under these conditions, our results suggest that the facilitation afforded by emotional targets, to a substantial extent, reflects the interplay between semantic feedback and relatively late, decision-based processes. In other words, emotional valence effects in the standard LDT may comprise two components: an early task-general effect that is preconscious, and a later task-specific effect that is mediated by feedback from semantically rich representations. This dissociation could potentially explain some of the anomalies in the literature. For example, studies examining the detection of briefly presented masked words have often revealed preferential access for negative, as compared to positive, words (Dijksterhuis & Aarts, 2003; Nasrallah et al., 2009), whereas valence effects are more symmetric when fully visible words are used (see, e.g., Kousta et al., 2009). Scott et al.'s (2009) ERP lexical decision study also revealed symmetric effects of valence in RT data, but an effect of valence *only* for high-frequency negative words in the earliest ERP component (P1).

To conclude, the present study is the first to use RT distributional analyses to provide finer-grained constraints on emotional valence effects in lexical decision. Moving forward, this work further underscores how distributional analyses can serve as a useful complement to mean-level analyses for understanding better the many other semantic richness dimensions in the literature.

Author note This research was carried out as an undergraduate honors thesis by C.S.S. under the direction of M.J.Y. Portions of this research were presented at the Association for Psychological Science, 24th Annual Convention (May 2012, Chicago, Illinois, USA).

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