The last course of coarse coding: Hemispheric similarities in associative and categorical semantic processing

Emily N. Mech [a,*], Padmapriya Kandhadai [b], Kara D. Federmeier [a,c,d]

[a] Department of Psychology, University of Illinois at Urbana-Champaign, United States
[b] Department of Computing Studies and Information Systems, Douglas College, Canada
[c] Program in Neuroscience, University of Illinois at Urbana-Champaign, United States
[d] The Beckman Institute for Advanced Science and Technology, University of Illinois at Urbana-Champaign, United States

ABSTRACT

To test theories that posit differences in how semantic information is represented in the cerebral hemispheres, we assessed semantic priming for associatively and categorically related prime-target pairs that were graded in relatedness strength. Visual half-field presentation was used to bias processing to the right or left hemisphere, and event-related potential (ERP) and behavioral responses were measured while participants completed a semantic relatedness judgement task. Contrary to theories positing representational differences across the cerebral hemispheres, in two experiments using (1) centralized prime presentation and lateralized targets and (2) lateralized primes and targets, we found similar priming patterns across the two hemispheres at the level of semantic access (N400), on later measures of explicit processing (late positive complex; LPC), and in behavioral response speeds and accuracy. We argue that hemispheric differences, when they arise, are more likely due to differences in task demands than in how the hemispheres fundamentally represent semantic information.

1. Introduction

The distinct processing capabilities and biases of each of the cerebral hemispheres has been of long-standing interest in the field of psychology, and specifically in the study of language. Although initial research emphasized the critical role of the left hemisphere (LH) for language (especially production), it is now known that both the LH and the right hemisphere (RH) play a role in language comprehension – albeit in different ways (for reviews see Krashen, 1976; Federmeier, Wlotko, & Meyer, 2008). For example, the LH has been found to use context information to rapidly predict and preactivate information that is likely to occur next in the sequence (reviewed in Federmeier, 2007). The RH, in contrast, maintains more veridical information about incoming stimuli (Evans & Federmeier, 2008) and can facilitate comprehension even when the information about the event in the language stream doesn't unfold in a predictable manner (Metusalem et al., 2012; Metusalem et al., 2016), as during the comprehension of jokes and other figurative language (e.g., Coulson & Wu, 2005; Diaz & Eppes, 2018). Given these differences that have been documented at the level of sentence or discourse processing, it is of interest to understand whether the source of these asymmetries comes from hemispheric specialization for more

basic aspects of processing, such as the activation of semantics in response to a word.

Many early studies of semantic priming at the word level utilizing the visual half-field method to bias process toward one hemisphere (for review, Banich, 2002) showed that both hemispheres manifest basic semantic priming effects, although the degree of priming can differ across the hemispheres depending on whether or not the specific task requires strategic meaning selection or integration (Burgess & Simpson, 1988b; Chiarello, 1985; Chiarello, Burgess, Richards, and Pollock, 1990; Eglin, 1987; Walker & Ceci, 1985). More fine-grained asymmetries in patterns of priming emerged as prime-target stimuli were manipulated to be closely or diffusely related. Some work found evidence that the RH better maintained activation of distant semantic relations of words and multiple meanings of words (e.g., Burgess & Simpson, 1988a, 1988b; Chiarello et al., 1990), a pattern that was seen as consistent with work showing RH advantages for the processing of non-literal language such as jokes, sarcasm and metaphors – aspects of language that arguably rely on linking diffusely related concepts for successful comprehension (e.g., Anaki, Faust, & Kravetz, 1998; Beeman & Chiarello, 1998; Burgess & Chiarello, 1996; Coulson & Wu, 2005). In contrast, LH advantages were observed for processing the meaning of strongly related word pairs and

the dominant meaning of ambiguous words (e.g., Chiarello et al., 1990; Burgess & Simpson, 1988a, 1988b; Faust & Lavidor, 2003).

From patterns like these, several theories have been proposed to explain the distinct capabilities of the left and right hemispheres for apprehending word meaning. A particularly prominent and long-standing view is the "Coarse Coding" hypothesis, which posits that the role of the RH is to coarsely code semantic information by activating a broad and rich semantic field in response to a given word, whereas the LH narrowly activates only the meaning of the word that is relevant to the context (Beeman, 1998; Jung-Beeman, 2005). Early support for coarse coding came from summation priming paradigms, in which participants read three primes that were all weakly related (white––ceremony–tuxedo) or unrelated (soap–tunnel–mouse) to a lateralized target word (wedding) (Beeman et al., 1994). The results showed more facilitation from these summation primes when the target was presented initially to the RH (in the left visual field; LVF). In a second experiment using one directly related prime surrounded by two unrelated primes, greater priming was found for initial presentation to the LH (in the right visual field; RVF). Follow-up studies testing the predictions of the coarse coding model have yielded mixed results. Some studies have shown evidence consistent with the idea that the RH derives more benefit from distantly or weakly related information (Faust & Kahana, 2002, Faust & Lavidor, 2003, Simpson, 1994, Titone, 1998), but other studies have failed to find support for coarse coding (Richards & Chiarello, 1995; Livesay & Burgess, 2003; Kandhadai & Federmeier, 2007; Kandhadai & Federmeier, 2008; Kandhadai & Federmeier, 2010). For example, using both lexical decision and semantic relatedness judgement tasks to assess whether summation priming would differ across the hemispheres, Kandhadai and Federmeier (2007) found no hemispheric differences in priming for either ambiguous or unambiguous targets in either task.

However, direct comparisons across studies that have supported the coarse coding hypothesis versus those whose outcomes are inconsistent with its predictions are complicated by the use of differing stimuli and data analyses (cf. Kandhadai & Federmeier, 2007). Additionally, response times collected in behavioral studies are end-state measures, and, as such, are likely to be influenced by many aspects of processing, including later stage decision making. Given that the predictions of the coarse coding hypothesis are focused on early aspects of semantic processing, better tests of the theory come from measures that can more directly tap into those critical mechanisms. Event-related potentials (ERPs) are a particularly useful tool for examining semantic processing with greater temporal and functional precision (for review see Federmeier, Wlotko, & Meyer, 2008). An additional benefit of ERP approaches when combined with visual half-field presentation is that they afford measurement of eye position (as eye movements are readily detected using electrodes placed near the eyes), allowing the experimenter to reject any trials during which the participant did not maintain central fixation and thus invalidated the requirements of the method.

Visual half-field ERP studies investigating semantic processing in each of the hemispheres have compared effects on the N400 and late positive complex (LPC) components. The N400 ERP component is a negative going wave that peaks around 400 ms after the presentation of a meaningful stimulus and has been linked to relatively automatic aspects of semantic access. N400 responses are reduced (become less negative) due to a wide variety of factors that facilitate semantic access, including semantic priming (for review, see Kutas & Federmeier, 2011). Thus, the N400 provides a useful metric by which to compare early aspects of semantic processing in each hemisphere and under differing task conditions. The LPC is a post N400 positivity with a posterior scalp distribution that has been linked to more explicit memory retrieval and strategic semantic processing (e.g., Olichney et al., 2000, Swaab et al., 1998, Van Petten and Kutas, 1991), making it a useful index for examining more controlled aspects of semantic processing in each of the hemispheres.

Further tests of the coarse coding hypothesis took advantage of these strengths of the ERP method to examine how each of the hemispheres

process semantic information. Kandhadai and Federmeier (2008) followed up on their behavioral work to test semantic activation in each of the hemispheres using lexical decision and semantic relatedness judgement tasks with summation primes that converged on a lateralized ambiguous or unambiguous target. The results aligned with the behavioral patterns: N400 priming effects in both tasks for targets in the two visual fields were equivalent for both the ambiguous and unambiguous conditions, countering the predictions of the coarse coding hypothesis (Kandhadai & Federmeier, 2008)[1].

As emerging evidence called into question the claims of the coarse coding hypothesis, patterns of priming in other ERP experiments led to new proposals about asymmetries in semantic representation. Deacon et al. (2004) found that the RH showed more N400 priming for word pairs that shared a category-based relationship, whereas the LH manifested more priming for associative relatedness. They proposed that these findings arose because semantic processing in the RH taps into a distributed semantic memory system based on semantic features, whereas the LH uses local, holistic representations that are connected with associative links (e.g., Deacon et al., 2004; Grose-Fifer & Deacon, 2004).

Again, however, the evidence in support of Deacon's Association/Category hypothesis has been mixed (Atchley & Kwasny 2003; Bouaffre & Faita-Ainseba, 2007; Coulson & Wu, 2005). For example, Bouaffre and Faita-Ainseba (2007) tested participants in a lexical decision task using both associatively and categorically related word pairs and measured both behavioral and ERP responses. Behavioral results demonstrated that there was a priming effect for associatively related stimuli in both hemispheres, whereas neither hemisphere showed a reliable behavioral priming effect for categorically related stimuli. The ERP findings were largely consistent with the behavioral results: Overall, priming was found only for the associatively related stimuli and was observed in both visual fields (on the N400 and the LPC for the LH and on the LPC for the RH). The fact that the RH did show priming for associative relationships is in conflict with the idea that only the LH uses representations that code these types of relations, and the hypothesized sensitivity of the RH to categorical relationships did not manifest in either the behavior or the ERP measures.

The numerous inconsistent results across this literature present a challenge in reconciling the empirical findings with the specific theories that have been proposed. Part of the difficulty is that the theories sometimes make overlapping predictions. The representational differences posited to underlie hemispheric asymmetries are importantly different in the Association/Category and Coarse Coding views. However, given that words and concepts that are categorically but not associatively related (e.g., Dog-Goat) may also be more diffusely semantically linked than concepts that are only associatively related (e.g., Dog-Bone), both accounts may be able to explain some of the observed patterns (Bouaffre & Faita-Ainseba, 2007). Dissociating these views requires that both the type and strength of relationship be manipulated in the same design, which, to our knowledge, has not previously been done. Thus, the current study was designed to fill that gap.

Moreover, although studies routinely lateralize the target, there is variability in whether the prime is also lateralized (e.g., Chiarello et al., 1987; Burgess & Simpson, 1988a, Marcel & Patterson, 1978). Some have argued that lateralizing the prime allows a stronger test of each hemisphere's processing capabilities/biases (e.g., Chiarello et al., 1990; Zaidel, White, Sakurai, and Banks, 1988). At the same time, however, given that lateralized words are harder to recognize, perhaps especially

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[1] Note that inferences about lateralization in visual half-field ERP studies are based on comparing effects for stimuli presented in the left and right visual half field (as in behavioral studies) and not on the scalp topography of the components, as scalp topography cannot be used to directly infer the laterality of neural sources.

with left visual field presentation (e.g., Jordan et al., 2000), lateralizing the prime may also weaken the experimental manipulation and/or disadvantage the right hemisphere solely due to factors related to word perception rather than sematic processing as such. Given that prime location has mattered for some outcomes (e.g., Chiarello et al., 1990), it is important to assess the theories using both approaches. Here, therefore, we present two experiments, one with central and one with lateralized primes.

At a more general level, both the Association/Category and Coarse Coding theories have in common that they postulate fundamental differences in how each hemisphere represents and/or organizes semantic information – differences that are thus presumed to hold across tasks and experimental parameters. As such, experimental patterns are taken to provide evidence about these (static) differences, and conflicts across studies are often thought to arise from contamination of the priming by aspects of processing other than the semantic activation mechanisms of interest. However, there have increasingly been proposals across domains suggesting that representations are not organized in a static fashion but, instead, must trade off stability with flexibility (e.g., Abraham and Robins, 2005; Cools, 2019; Musslick et al., 2018). Insight from the simulation of unilateral and bilateral damage to the cerebral hemispheres additionally demonstrates that widespread *redundancy* across the hemispheres allows relatively preserved functioning (Schapiro, McClelland, Welbourne, Rogers, & Lambon Ralph, 2013). Thus, rather than simply postulating representational differences across the hemispheres, contemporary work suggests that characterizing semantic processing in the cerebral hemispheres requires accounting for both how semantic information is represented and how control processes are brought to bear to shape the use of that information in a particular context (De Deyne, Kenett, Anaki, Faust, & Navarro, 2017; Lambon Ralph, Jeffries, Pattersion, & Rogers, 2017). Specifically, the way in which semantics is processed may not only be revealed by the task in which it is measured, but, critically, depend upon it (e.g., Willits, Amato, & MacDonald, 2015).

A semantic system that is warped to process information in a task-dependent manner would be adept in meeting the demands of a variety of tasks and contexts. Pragmatically, on this view of semantic processing, conflicting results are not surprising but are actually expected when studies use different experimental tasks and protocols. Asymmetries – and especially differing patterns of asymmetries across tasks – may then arise, not because of fundamental differences in semantic representation or processing, but because the hemispheres differ in how or how flexibly they respond to task demands. For example, Kandhadai and Federmeier (2010a,b) showed that although the LH was more likely to strategically reshape meaning activations (as indexed by LPC patterns) in passive tasks where the semantic relationships were task-incidental, tasks that explicitly drew attention to semantic relations yielded no LPC asymmetries (N400 priming patterns were similar across the hemispheres in both task conditions). These results suggest that both hemispheres are capable of engaging controlled semantic processing but differ in how much task support they require to do so.

Despite the lack of consistent empirical support for theories positing fundamental asymmetries in semantic processing, these views – and especially Coarse Coding theory – continue to have an important impact on the field, shaping how people think about a broad range of topics including, for example, the comprehension of nonliteral language (Mitchell, Vidaki, & Lavidor, 2016), brain damage and rehabilitation (Blake, Tompkins, Scharp, Meigh, & Wambaugh, 2015), and second language learning (Faust, Ben-Artzi, & Vardi, 2012). Thus, it is important to arbitrate whether there are basic hemispheric differences in semantic representation and/or activation that determine processing outcomes, or whether, instead, asymmetries arise primarily when similar semantic representations and access processes are differentially shaped by task demands.

1.1. The present study

The present study was designed to test four key questions in the literature within a single, within-subjects design; do the hemispheres fundamentally differ in how they represent meaningful information that varies in 1) strength 2) or type of relatedness? Do the hemispheres differ in 3) automatic vs. controlled processing of semantic information, and finally, does 4) prime lateralization impact the assessment of semantic processing across the hemispheres? To that end, we combined visual half-field presentation methods with the measurement of ERPs as participants viewed primes and lateralized targets. Primes and targets were related either categorically or associatively, and, across both relation types, were strongly related, weakly related, or unrelated. The Association/Category hypothesis predicts that, irrespective of the strength of the relationship, we should observe N400 priming for associative relationships exclusively or primarily in the LH and N400 priming for category relationships in the RH. The strength manipulation, then, allows a direct test of the Coarse Coding hypothesis. Coarse Coding predicts that, irrespective of relationship type, the LH should primarily be sensitive to strong relatedness and thus should treat weak and unrelated pairs similarly. Correspondingly, the RH should have an advantage for priming from weakly related pairs of either type and should show more similarity in priming across strong and weak pairs. In contrast, we hypothesize that the hemispheres share the basic ability to appreciate the full range of semantic relation type and strength. Thus, we predict that we will find identical priming patterns in each hemisphere, with the largest N400s to the unrelated pairs, the smallest N400s to the strongly related pairs, and N400s of intermediate size for the weakly related pairs, for both relation types.

Whereas N400 effects, which are thought to arise from initial, implicit semantic activations (see review in Kutas & Federmeier, 2011), tend to be relatively stable across tasks, the LPC reveals more explicit, controlled aspects of processing and is more likely to differ based on task demands. Following Kandhadai and Federmeier (2010b), we used an explicit semantic relatedness judgment task to increase the likelihood that both hemispheres would be encouraged to employ strategic semantic processing, allowing us to assess, via the LPC, their relative abilities to do so when required. Across two experiments we also examined priming onto lateralized targets from centrally presented primes (Experiment 1) and from laterally presented primes (Experiment 2). As discussed, these approaches trade-off prime visibility (better for central prime presentation) and the "purity" of the induced hemispheric bias (argued to be higher for lateralized prime presentation; e.g., Chiarello et al., 1990; Chiarello & Richards, 1992). If the precision of the induced hemispheric bias is decreased with central prime presentation, asymmetries in priming should be greater with lateral prime presentation. Alternatively, if central and lateral prime presentation are commensurate for measuring semantic processing in each hemisphere, it is possible that the result pattern will be similar across Experiment 1 and Experiment 2, perhaps with slightly lower effect sizes in Experiment 2 due to poorer prime perceptibility. Again, the goal of both of these experiments is to use the N400 and LPC as an index of automatic and controlled semantic processing, respectively, to test whether the hemispheres contribute differentially to processing of word pairs that are either associatively or categorically related and that vary in the strength of their relatedness.

2. Experiment 1

2.1. Method

2.1.1. Participants

24 participants (12 female) were recruited from the student population at the University of Illinois, consented to participate, and were compensated with course credit. Participants ranged in age from 18 to 26 years ($M = 20.2$) and were right-handed as indexed by the Edinburgh

handedness inventory, in which positive laterality quotients (maximum: 100) indicate right-handedness (*M* = 79.6, range = 45–100) (Oldfield, 1971). 13 participants reported having left-handed family members. Participants were not exposed to a language other than English before the age of 5. Additionally, participants were screened for normal vision and had no history of neuropsychological or psychiatric disorders.

2.1.2. Materials

Participants were presented with prime-target word pairs that were either related by association or by category membership (see Table 1 for examples). Within both types of relatedness, prime-target pairs were designated as strongly related, weakly related, or unrelated. Categorically related pairs were chosen from published category norms (Battig & Montague, 1969; Hampton & Gardiner, 1983; Hunt & Hodge, 1971; McCloskey & Glucksberg, 1978; McEvoy & Nelson, 1982; Shapiro & Palermo, 1970; Van Overschelde, Rawson, & Dunlosky, 2004). For strongly related pairs, both the prime and target words were among the most common responses to the same category cue (average response proportion = 0.53; range 0.23–1 for all primes and strongly related targets), were the single response given to the category prompt, or were both rated as highly typical for a particular category (typicality rating always < 1 unit away from maximum). For weakly related pairs, primes again had high response proportions or typicality for a particular category; targets were produced (or rated) as a member of the category, but with lower response proportion (average 0.04; range 0.003–0.08) or typicality ratings (>2 units away from maximum). Matched unrelated pairs did not co-occur in the category norms and were judged as unrelated by category by three experimenters.

Associatively related pairs were chosen from the University of South Florida association norms (Nelson, McEvoy & Schreiber, 2004). Strongly

Table 1

Example prime-target pairs related by category or association and varying in relatedness strength.

Type	Strength	Prime	Target
Category	Strong	DOG	COW
		VULTURE	HAWK
		DOCTOR	TEACHER
		JAZZ	COUNTRY
		UNDERWEAR	SOCK
		SOCCER	HOCKEY
	Weak	TIGER	HAMSTER
		FALCON	OSTRICH
		LAWYER	ATHLETE
		RAP	GOSPEL
		SHIRT	MITTENS
		BASEBALL	DIVING
	Unrelated	TABLE	SHEEP
		CENTURY	PIGEON
		DRIER	ASTRONAUT
		RAT	POETRY
		TREE	BLAZER
		OLIVE	LAW
Association	Strong	CRAWL	BABY
		BUTCHER	MEAT
		WASP	STING
		LICENSE	DRIVE
		PILLOW	SLEEP
		VELVET	SOFT
	Weak	FAIL	CLASS
		COLONEL	RANK
		KITTEN	CUTE
		CAMPAIGN	VOTE
		TICKET	COP
		BOOTS	MUD
	Unrelated	LABEL	MOPS
		TROOPER	PROJECT
		SPEAR	BAD
		PROSE	DAM
		BEDROOM	SKY
		FOAM	HAPPY

related pairs had an average forward association strength of 0.43 (range 0.3–0.81); this number reflects the proportion of people who gave the target word as an association of the prime word). Weakly related pairs had an average forward association strength of 0.02 (range 0.01–0.03). Unrelated targets were never given as an associate of the prime. Importantly, all items that were related by association were not categorically related and all items that were related by category were not associated, using the same norms and criteria (unrelated pairs were neither categorically nor associatively related). All word pairs within a type (categorically and associatively related and their corresponding unrelated items) were matched for word length (average length: association (5.1), category (5.75)) and frequency (average log frequency: association (1.43), category (1.02)) (Francis & Kucera, 1967) and primary part of speech.

Stimuli were presented in four experimental lists that counterbalanced participant gender, and response hand. Each word pair was presented only once per list and, across lists, each word pair was presented an equal number of times to the left and right visual field. Twenty-nine associatively related and twenty-six categorically related pairs of each strength of relatedness were presented in each visual field across three blocks. In total, each participant was presented with 330 pairs during the experiment.

2.1.3. Procedure

Participants were tested in a dim and quiet testing room and were seated 40″ from a 21″ SVGA monitor on which the experimental stimuli were presented. Stimuli were presented in white capital letters on a black background. Each trial began with a series of fixation crosses, "++++", presented in the center of the screen for 500 ms. The interstimulus interval (ISI) was jittered to reduce anticipatory potentials and lasted between 300 and 800 ms. Following the ISI, a prime was presented centrally on the screen for 200 ms. Another 300 ms ISI followed, and then the target was presented at the vertical center and lateralized with its medial edge two degrees from the horizontal center. Targets subtended 2.8 degrees of horizontal visual angle (range: 1.3 to 4.3 degrees) and 0.68 degrees of vertical visual angle. The target remained on the screen for 200 ms. Participants were told that once the target disappeared they should press a button to indicate, as quickly as possible, whether or not they judged the prime and target to be "related"; instructions emphasized that participants should be open to multiple ways in which words could be related to one another and that there were no correct answers, so they should just use their best judgment. Following their response, the prompt, "!!!!", appeared on the screen and gave participants 1500 ms to blink and prepare for the next trial.

2.1.4. Data collection

EEG was recorded from 26 Ag/AgCl electrodes arranged in an equidistant configuration on the electrode cap, with the online reference placed on the left mastoid. Additionally, electrodes were placed on the outer canthus of each eye and on the left infraorbital ridge to record saccades and blinks. Electrode impedances were maintained below 3 k-Ohms. A Sensorium 32 channel polygraph set to a band pass of 0.02–100 Hz with a sampling rate of 250 Hz amplified the brain potentials.

2.1.5. Data analysis

The EEG data were extracted at a single trial level, and a low pass filter of 30 Hz was applied to the raw data. Artifact rejection for amplifier blocking, saccades, blinks, and excessive muscle activity was applied offline before averaging (see Table 3 for the number of trials in each condition). Data were epoched from –100 to 900 ms post-stimulus-onset and were re-referenced to the average of the left and right mastoids and baseline corrected using the 100 ms prior to stimulus onset. To create a single trial mean amplitude, voltages were averaged across 8 medial central electrodes (RMFr, LMFr, LMCe, RMCe, MiCe, MiPa,

LDPa, RDPa) over the time window of 300–500 ms for the N400 data, and across 9 medial centro-posterior electrodes over the time window of 600–900 ms for the LPC (LMCe, RMCe, MiCe, MiPa, LDPa, RDPa, LMOc, RMOc, MiOc).

Mean amplitudes calculated for each trial and each component were modeled with linear mixed effects models estimated via maximum likelihood in the lme4 package (Bates, Mächler, Bolker & Walker, 2015) of R (R Core Team, 2020, version 4.0.2). Models were fit according to an analytic strategy developed both from the theoretical questions being tested and as suggested by data visualization. First, descriptive statistics were calculated, and the data were visualized both by participant and by condition. Next, a null model with random intercepts for participants and items was fit to examine the nesting structure of the data. A model fitting procedure was then followed such that first intercept-only models were fit to specify the fixed effects structure. Models were built starting with the factored experimental conditions as main effects, and models were subsequently built to test the whether the interactions predicted by each theory improved model fit. Once the fixed effects structure was specified in the best fitting model as determined by regular chi square deviance tests (Snijders & Bosker, 2012), random slopes for each experimental condition were added to this model and tested against a mixture chi square distribution to determine if additional random effects improved model fit (Stram & Lee 1994, 1995). Following this iterative model testing procedure, the best fitting model was selected as suggested by the chi square deviance test, and fixed effects were assessed against sandwich (robust) standard errors to assess whether the fixed effects structure was appropriately specified (Snijders & Bosker, 2012). [2] This modeling strategy was employed to analyze both the N400 and LPC components.

2.2. Results

2.2.1. Behavioral and ERP descriptive statistics

Descriptive statistics from participants' behavioral responses are reported in Table 2. On average, participants judged pairs in the strongly related conditions to be "related" more than 80% of the time, for both types of relations and in both visual fields. This attests that they were able to see the lateralized target and respond appropriately. Consistent with the graded manipulation of relatedness, weakly related items were less likely to be judged as related, and unrelated items were very unlikely to be judged as related, again for both relation types and in both visual fields. Response times (RTs) to make these judgements followed a similar, graded pattern: In all conditions and visual fields, RTs were fastest for strongly related items, intermediate for weakly related items, and slowest (to, primarily, respond "no") to unrelated items.

Means, standard errors, and 95% confidence interval are reported for the mean amplitudes of the N400 and LPC components by condition in Table 3. Fig. 1 shows ERPs at each of the medial electrodes for stimuli presented to each visual field and relatedness type (see Appendix A for ERPs plotted across all channels for both visual fields and relatedness types).

2.2.2. Behavioral results

We assessed whether there were reliable differences in participants' behavioral responses across Type (association, category), Strength (strong, weak, unrelated), and Visual Field (RVF, LVF) by fitting a multiple linear regression model for relatedness judgements and response times. In both models, Type, Strength, and Visual Field were

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treatment coded and were entered into the model as predictors. Association, strong, and LVF factor levels were designated as reference levels for Type, Strength, and Visual Field predictors. Additionally, to test the critical questions about hemispheric differences, interactions of Type with Visual Field and Strength with Visual Field were entered into each model.

The relatedness judgement model results are reported in full in Table 4. The model of relatedness judgement behavior accounted for 37% of the variance in response behavior, $F(7, 280) = 25.09$, $p < .001$, adjusted $R^2 = 0.37$, 95% CI R^2 [0.30, 0.47]. Results suggested that endorsements of relatedness were stronger for pairs related by association than by category. Participants endorsed strongly related pairs as being "related" to a greater degree than they endorsed weakly related pairs as "related." The interactions of Type and Visual Field as well as Strength and Visual Field did not reach significance.

Table 4 also includes all response time model results. Note that, because these were subjective judgments, particular answers are not "right" or "wrong," and we therefore used all responses in the analyses. The response time model accounted for 14% of the variance in response times, $F(7, 280) = 7.81$, $p < .001$, adjusted $R^2 = 0.14$, 95% CI R^2 [0.09, 0.24]. The results suggest that response times did not differ by Type or by Visual Field. Response times were fastest for strongly related pairs, intermediate for weakly related pairs, and slowest for unrelated pairs. The interactions of Type and Visual Field and Strength and Visual Field did not reach significance in the model.

2.2.3. Model results of the N400

We fit a series of models to test whether the mean amplitude of the N400 would differ across the hemispheres with regard to prime-target Type (association, category), Strength of relatedness (strong, weak, unrelated), and Visual Field (RVF, LVF). All predictors were treatment coded with association, strong, and LVF designated as reference levels for Type, Strength, and Visual Field predictors respectively, and the output of all of the models tested is reported in Appendix B. First, we fit a null model to the data and found that the intraclass correlation coefficient (ICC) of the model was 0.09, suggesting that the nesting of trials in participants led to slightly more similarity of mean amplitudes across trials within participants than between participants.

We next fit a Base Model to test whether our manipulated condition variables improved the fit of the null model and found that Type, Strength, and Visual Field significantly improved the fit of the model to the data ($\chi^2 = 176.69$, $df = 4$, $p < .001$). To test the Association/Category hypothesis and the Coarse Coding hypothesis in the same model, we fit a Type and Strength Interaction Model that added interactions of Type and Visual Field and Strength and Visual Field. Model comparison suggested that the Type and Strength Interaction Model did not fit the data better than the Base Model ($\chi^2 = 0.23$, $df = 3$, $p = .97$). However, although interactions predicted by the Association/Category and Coarse Coding hypotheses together did not improve the model fit, it is possible that including one of the interactions by itself could provide a better fit to the data. Therefore, we tested the Type Model that included a Type and Visual Field interaction and the Strength Model that included a Strength and Visual Field interaction against the Base Model, and we found that neither interaction improved the model fit (Type: $\chi^2 = 0.16$, $df = 1$, $p = .69$; Strength: $\chi^2 = 0.07$, $df = 2$, $p = .96$).

Following the specification of the fixed effects structure, we tested whether including random slopes for Type, Strength, and Visual Field would improve model fit. The Base Model that included a random slope for Type did not improve model fit over the random intercept model ($\chi^2 = 4.42$, $p = .07$), nor did including a random slope for Visual Field ($\chi^2 = 3.21$, $p = .14$). The Base Model including a random slope for Strength did not converge. As interpretations of the fixed effects did not change between the random intercept and slope models, and as models that included random slopes did not improve model fit, the most parsimonious and best fitting model as determined by deviance and AIC was the Base Model with only random intercepts for participant and item.

Table 2
Mean percentage (with standard error and 95% confidence intervals) of relatedness endorsements and mean response time to make the relatedness judgement for each condition in each VF.

Type	VF	Strength	Relatedness Judgements (% Endorsed)			Response Time (ms)		
			Mean	SE	95% CI	Mean	SE	95% CI
Association	LVF	Strong	92.51	1.15	2.38	764.59	36.07	74.62
		Weak	68.85	3.02	6.24	922.37	51.49	106.51
		Unrelated	19.54	3.65	7.56	1129.86	82.85	171.38
	RVF	Strong	94.54	1.19	2.46	732	39.27	81.24
		Weak	75.76	3.44	7.12	881.95	57.69	119.34
		Unrelated	19.41	4.5	9.31	1077.91	65.27	135.03
Category	LVF	Strong	81.08	2.63	5.45	852.67	52.07	107.72
		Weak	49.68	3.53	7.31	1011.66	60.12	124.37
		Unrelated	16.51	3.43	7.1	1105.11	81.32	168.22
	RVF	Strong	88.87	1.51	3.12	788.6	41.52	85.89
		Weak	52.36	3.76	7.78	990.79	78.87	163.16
		Unrelated	15.43	3.83	7.92	1070.04	70.79	146.45

Table 3
Mean N400 and LPC amplitudes (with standard errors and 95% confidence intervals) for each condition in each VF. N reflects the number of trials averaged after artifact rejection in each condition in each VF (N trials before artifact rejection: Association (696), Category (624)).

Type	VF	Strength	N400				LPC			
			N	μV	SE	95% CI	N	μV	SE	95% CI
Association	LVF	Strong	556	6.27	0.4	0.79	556	9.77	0.42	0.83
		Weak	564	2.76	0.38	0.74	564	7.51	0.41	0.8
		Unrelated	561	0.83	0.38	0.74	561	5.33	0.42	0.82
	RVF	Strong	542	6.8	0.41	0.8	542	9.66	0.42	0.82
		Weak	578	4.08	0.39	0.78	579	8.37	0.39	0.77
		Unrelated	550	1.66	0.39	0.77	550	5.55	0.4	0.78
Category	LVF	Strong	486	3.62	0.43	0.85	486	8.94	0.47	0.92
		Weak	510	1.13	0.43	0.84	510	6.64	0.44	0.86
		Unrelated	524	−0.24	0.39	0.77	523	5.27	0.41	0.8
	RVF	Strong	506	4.40	0.41	0.81	507	8.67	0.43	0.85
		Weak	512	1.7	0.42	0.83	512	6.78	0.45	0.89
		Unrelated	511	0.59	0.4	0.78	494	5.88	0.41	0.8

Additionally, we examined the residuals of the final model to check the assumptions of linearity, normality, and homoscedasticity, and they did not suggest any violated assumptions.

Fig. 2 shows the Base Model predicted estimates for Type, Strength, and Visual Field. Estimates of the fixed effects in the Base Model suggested that mean amplitudes to categorically related pairs were more negative overall in the N400 time window than amplitudes to associatively related pairs, suggesting that priming was generally greater for stimuli that share only an associative relationship compared to those that share only a categorical relationship (cf. Bouaffre & Faita-Ainseba, 2007). Consistent with the graded manipulation of Strength, mean amplitudes to strongly related prime-target pairs were more positive (facilitated N400s) than to weakly related and unrelated pairs. Follow-up contrasts further showed that weakly related pairs were also facilitated compared to unrelated pairs ($F(1, 335.23) = 25.82$, $p < .001$). Finally, ERPs were overall more positive for RVF than for LVF presentation. The estimates of the fixed effects of Base Model and the Type and Strength Model are reported in Table 5.

*2.2.4. Model results of the LPC*

To test the same predictions for the LPC, we again fit a series of models with the aforementioned predictors and coding scheme. The ICC of the null model was 0.05. We fit models in the same sequence as described in the N400 Model results, and we found that the Base Model improved the model fit over the null model ($\chi^2 = 125.44$, $df = 4$, $p < .001$). As was found for the N400, the Type and Strength Interaction Model, the Type Model, and the Strength Model all did not improve model fit over the Base Model (Type and Strength: $\chi^2 = 0.97$, $df = 3$, $p = .81$; Type $\chi^2 = 0.15$, $df = 1$, $p = .70$; Strength: $\chi^2 = 0.82$, $df = 2$, $p = .66$).

After choosing the fixed effects structure, we tested whether including random slopes for Type, Strength, and/or Visual Field would improve model fit. Including a random slope for Type or Visual Field did not improve model fit (Type: $\chi^2 = 0.45$, $p = .65$; VF: $\chi^2 = 1.15$, $p = .42$). However, the model fit significantly improved by including a random slope for Strength ($\chi^2 = 42.11$, $p < .001$).

Therefore, the Base Model with a random slope for Strength was chosen as the best fitting model based on the deviance tests and parsimony. Similar to the N400 fixed effects estimates, mean amplitudes were more positive for the associatively related pairs than the categorically related pairs. Again, we observed a graded effect of the Strength manipulation. Strongly related pairs elicited more positive responses than weakly related and unrelated pairs, and follow-up contrasts indicated that weakly related pairs were more positive than unrelated pairs ($F(1, 29.74) = 20.62$, $p < .001$). Fig. 2 shows the final LPC model predicted estimates of Type, Strength, and Visual Field, and Table 5 shows the estimates of the fixed effects for the Base Model with a random slope for Strength as well as the Type and Strength Interaction Model.

2.3. Discussion experiment 1

The results from modeling the effects of Type, Strength, and Visual Field on both the N400 and LPC components revealed that in this semantic relatedness judgment task the left and right hemispheres processed the prime-target pairs similarly, with both hemispheres showing clear sensitivity to both types of relations. On the N400, an ERP component that has been linked to early, relatively automatic aspects of semantic access, the pattern of mean amplitude across the relatedness types (association, category) and the relatedness strengths (strong,
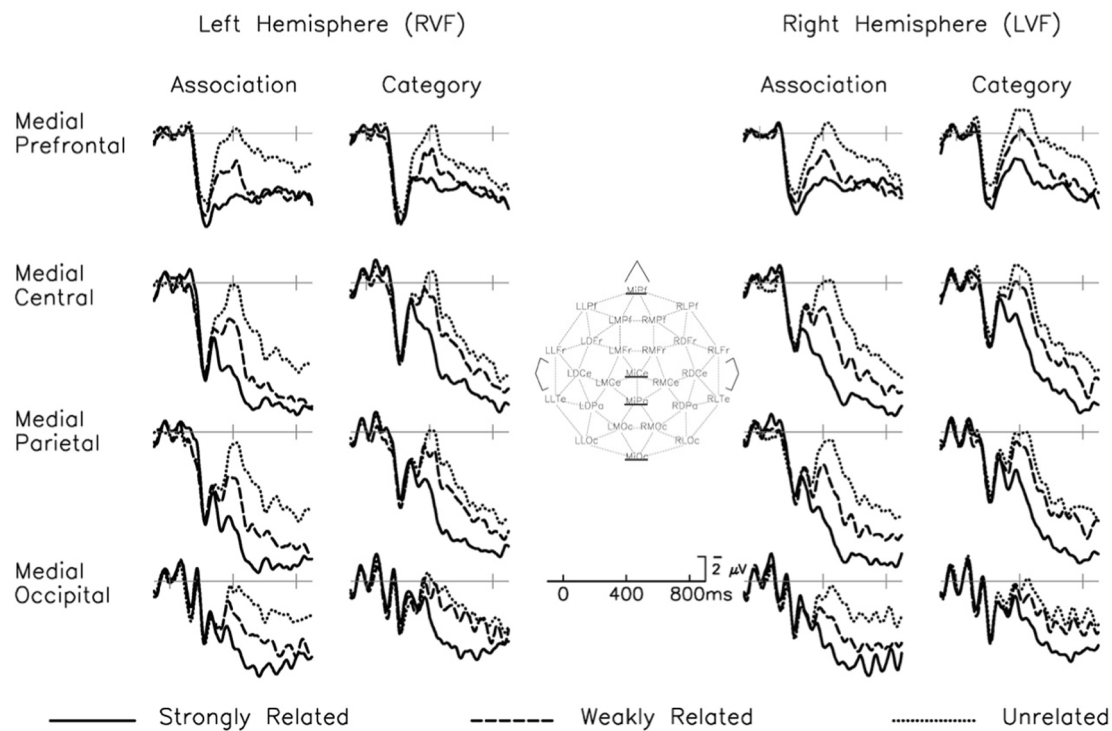
Fig. 1. Grand averages for each level of prime-target relatedness, condition, and Hemisphere/VF of stimulus presentation are plotted at the four medial electrode sites (underlined). Across all comparisons and in both the N400 (300–500 ms) and LPC (600–900 ms) time windows, strongly related pairs elicited the most priming, followed by weakly related, and then unrelated pairs.

Table 4
Model estimates of relatedness judgements and response times with 95% confidence intervals and p-values. The intercept reflects the mean at the reference levels of association, strong, and LVF. Predictor estimates reflect the difference between the reference level and the factor level in parenthesis.

Predictors	Relatedness Judgements			Response Time (ms)		
	Estimates	*95% CI*	*p*	*Estimates*	*95% CI*	*p*
Intercept	91.39	86.07–96.71	<0.001	783.20	684.21–882.18	<0.001
Type (Category)	−9.19	−14.51–−3.87	0.001	50.87	−48.11–149.86	0.313
VF (RVF)	4.50	−3.03–12.02	0.240	−49.16	−189.15–90.83	0.490
Strength (Unrelated)	−4.82	−11.33–1.70	0.147	308.85	187.62–430.09	<0.001
Strength (Weak	−27.53	−34.04–−21.01	<0.001	158.38	37.15–279.62	0.011
Type (Category): VF (RVF)	0.83	−6.70–8.35	0.829	1.65	−138.34–141.64	0.981
VF (RVF): Strength (Unrelated)	−4.31	−13.53–4.91	0.358	4.82	−166.63–176.27	0.956
VF (RVF): Strength (Weak)	−0.11	−9.33–9.10	0.981	17.69	−153.76–189.14	0.839
Observations	288			288		
R^2 / R^2 adjusted	0.385 / 0.370			0.163 / 0.142		

weak, unrelated) was remarkably similar across visual field. Contrary to the predictions of the Coarse Coding hypothesis, which posits that weakly related pairs should be primed primarily or exclusively with RH/LVF presentation, we found that weakly related pairs were also primed in the LH/RVF and that the pattern of priming for weakly related items was similar in the two visual fields across both types of relationship. Similarly, we failed to find support for the Association/Category hypothesis, which predicted that priming for associated but not categorically related stimuli would be seen exclusively or primarily in the LH/RVF and priming for categorically but not associatively related stimuli in the RH/LVF. Instead, our results show that both hemispheres prime in a similar and graded fashion for targets related either by association or by category.

The LPC was analyzed to examine whether the Coarse Coding and Association/Category hypotheses might be supported when assessed with a component that has been linked to more explicit and controlled aspects of semantic processing. However, the predictions of both

hypotheses were also not supported by our LPC results. As with the N400, in both visual fields the LPC showed greatest priming for strongly related primes, followed by weakly and then unrelated primes, and there was LPC priming for both association and category relatedness types. Finally, end-stage behavioral measures also did not reveal processing asymmetries, in either accuracy or response time.

Therefore, considering the results across all measures, we do not find any evidence for basic differences in the representation or organization of semantic information across the cerebral hemispheres. Here, we used a semantic relatedness judgement task that demanded explicit appreciation of the semantic relationships, allowing us to assess whether both hemispheres can appreciate these relationships when the task calls for it – and it seems they can.

However, it is possible that the pattern of results on the target word was influenced by the central presentation of the prime. By presenting the prime centrally, both hemispheres are given the prime information, opening up the possibility of greater contribution from the contralateral
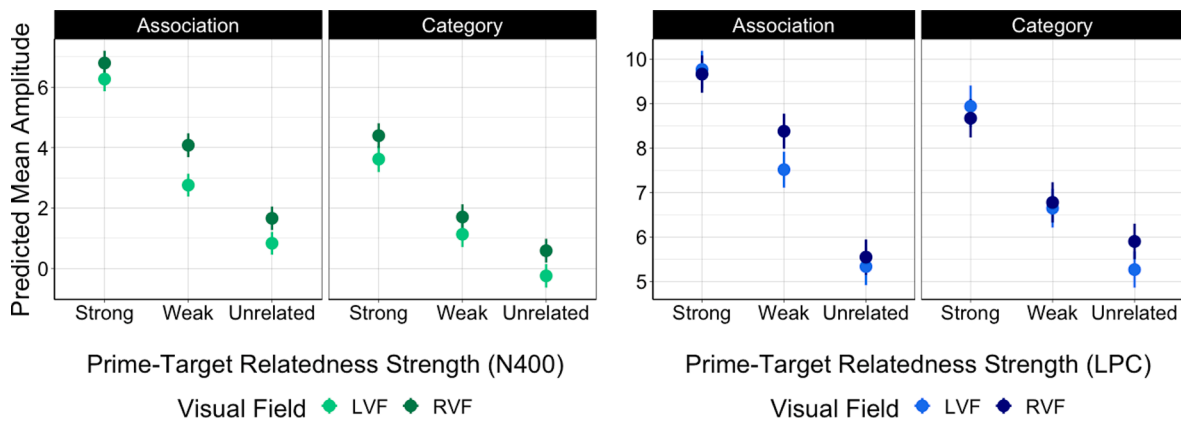
Fig. 2. Plotted are predicted mean amplitudes from the best fitting models of the N400 and LPC. For both the N400 and LPC and across each condition and VF, strongly related prime-target pairs are most facilitated, followed by weakly related and unrelated pairs, respectively.

Table 5
Estimates of the fixed effects for the best fitting models for the N400 and LPC and the comparison models including interactions of the Type and Strength predictors. Under each estimate, 95% confidence intervals are reported in square brackets and standard errors are reported in parentheses. Association (Type), strong (Strength) and LVF (Visual Field) were coded as reference levels, and for each predictor, the level in parentheses indicates what factor level is being compared to the reference.

Predictors	Base Model (N400) Estimates	t	Strength and Type Model (N400) Estimates	t	Base Model with Strength Slope (LPC) Estimates	t	Strength and Type Model (LPC) Estimates	t
(Intercept)	5.87 ***	8.79	5.84 ***	8.42	9.59 ***	10.20	9.70 ***	10.81
	[4.56–7.18] (0.67)		[4.48–7.20] (0.69)		[7.74–11.43] (0.94)		[7.94–11.46] (0.90)	
Visual Field (Right)	0.81 ***	3.71	0.87 *	2.01	0.21	0.99	0.00	0.01
	[0.38–1.23] (0.22)		[0.02–1.72] (0.43)		[−0.21–0.64] (0.22)		[−0.85–0.86] (0.43)	
Strength (Unrelated)	−4.72 ***	−13.01	−4.70 ***	−10.45	−3.88 ***	−6.73	−4.12 ***	−9.76
	[−5.43–−4.01] (0.36)		[−5.58–−3.82] (0.45)		[−5.01–−2.75] (0.58)		[−4.95–−3.29] (0.42)	
Strength (Weak)	−2.88 ***	−7.95	−2.93 ***	−6.51	−1.96 ***	−4.86	−2.20 ***	−5.21
	[−3.59–−2.17] (0.36)		[−3.81–−2.05] (0.45)		[−2.75–−1.17] (0.40)		[−3.03–−1.37] (0.42)	
Type (Category)	−1.83 ***	−6.19	−1.74 ***	−4.75	−0.70 **	−2.62	−0.60	−1.74
	[−2.41–−1.25] (0.30)		[−2.46–−1.03] (0.37)		[−1.22–−0.18] (0.27)		[−1.28–−0.08] (0.34)	
Visual Field (Right): Strength (Unrelated)			−0.04	−0.07			0.38	0.71
			[−1.08–1.01] (0.53)				[−0.67–1.44] (0.54)	
Visual Field (Right): Strength (Weak)			0.10	0.19			0.45	0.85
			[−0.94–1.14] (0.53)				[−0.60–1.50] (0.54)	
Visual Field (Right): Type (Category)			−0.17	−0.39			−0.17	−0.38
			[−1.02–0.68] (0.43)				[−1.02–0.69] (0.44)	

* p < 0.05 ** p < 0.01 *** p < 0.001

hemisphere on the processing of the target. Some past work finding differences in priming has been conducted with lateralized primes (e.g., Chiarello et al., 1990; Chiarello, 1985; Michimata, 1987). Thus, in a second experiment, using the same materials and design as Experiment 1, we set out to see if asymmetries might emerge when a single hemisphere is presented with both the prime and the target.

3. Experiment 2

3.1. Method

3.1.1. Participants

24 participants (12 female) were recruited from a midwestern university, consented to participate, and were compensated with course credit. Participants ranged in age from 18 to 24 years (M = 20.6) and were right-handed as indexed by the Edinburgh handedness inventory (M = 87.0, range = 50–100) (Oldfield, 1971). 14 participants reported left-handed family members. Participants were not exposed to a

language other than English before the age of 5. Additionally, participants were screened for normal vision and had no history of neuropsychological or psychiatric disorders.

3.1.2. Materials and procedure

The materials of Experiment 2 were identical to Experiment 1. The procedure differed only in that the primes were also now presented with nearest edge subtending 2 degrees to the left or right of fixation. For critical stimuli, prime and target locations always matched. However, to ensure that target VF was not predictable from prime VF, crossed VF prime-target filler pairs were included in which the prime and target were presented in opposite VFs. Filler pairs were constructed to be matched in frequency and length to both Association and Category prime-target related pairs. The related fillers were related either by association or by category to ensure that the addition of fillers did not change the probability of relation type. In total, 110 related filler pairs and 110 unrelated filler pairs were added. As we had no predictions about these pairs, we did not analyze the fillers. Thus, as in Experiment 1, each participant was presented with 330 critical pairs during the experiment.

3.2. Results

3.2.1. Behavioral and ERP descriptive statistics

Participants' behavioral responses are reported in Table 6, and descriptive statistics for the N400 and LPC components by condition are reported in Table 7. Fig. 3 shows ERPs at each of the medial electrodes for stimuli presented to each visual field and relatedness type (see Appendix A for ERPs plotted across all channels for both visual fields and relatedness types). One potential concern was that the lateralization of both the prime and target would make it difficult for the participants to see the stimuli and perform the task. However, participants endorsed the strongly related pairs as "related" on average 75% of the time. While slightly more variable than Experiment 1, the percentage of participants who endorsed the pairs as being related largely mirrored the graded pattern of relatedness. Response times to judge relatedness (as in Experiment 1, including all responses) similarly followed the graded relatedness pattern, with fastest responses to strongly related items, intermediate responses to weakly related stimuli, and slowest responses to unrelated stimuli. Collectively, this behavioral evidence suggests that although lateralizing the prime likely increased task difficulty, the participants were able to see the stimuli and respond appropriately.

3.2.2. Behavioral results

Analysis of the behavioral data proceeded as in Experiment 1. We tested behavioral responses across Type (association, category), Strength (strong, weak, unrelated), and Visual Field (RVF, LVF) with

multiple linear regression models for relatedness judgements and response times. Type, Strength, and Visual Field were treatment coded, and these predictors as well as interactions of Visual Field with Type and Visual Field with Strength were entered into each model. As in Experiment 1, association, strong, and LVF factor levels were designated as reference levels for Type, Strength, and Visual Field predictors.

The model results of the relatedness judgements are reported in Table 8. 20% of the variance in relatedness judgements was accounted for in the model, $F(7, 280) = 11.42, p < .001$, adjusted $R^2 = 0.20$, 95% CI R^2 [0.14, 0.30]. Relatedness was more strongly endorsed for pairs related by association than by category as well as for pairs presented to the RVF/LH than the LVF/RH. Participants' judged strongly related pairs as being "related" to a greater degree than they endorsed weakly related pairs as "related." The interaction of Type and Visual Field did not reach significance. An interaction of Strength and Visual Field suggested that the difference in relatedness judgements between strongly related and unrelated pairs was more pronounced in the RVF/LH than in the LVF/RH.

Table 8 also includes the response time model results. The response time model accounted for 9% of the variance in response times, $F(7, 280) = 5.09, p < .001$, adjusted $R^2 = 0.09$, 95% CI R^2 [0.05, 0.18]. The results suggest that response times did not differ by Type or by Visual Field. However, response times were fastest for strongly related pairs, numerically slower for weakly related pairs, and slowest for unrelated pairs. The interactions of Type and Strength with Visual Field did not reach significance in the model.

3.2.3. Model results of the N400

As in Experiment 1, we fit a series of models to test whether the mean amplitude of the N400 would differ across the hemispheres with regard to prime-target Type (association, category), Strength of relatedness (strong, weak, unrelated), and Visual Field (RVF, LVF). Again, predictors were treatment coded with association, strong, and LVF designated as reference levels, and the output of all models tested is reported in Appendix B. First, we fit a null model to the data; the intraclass correlation coefficient (ICC) of the model was 0.04. We next fit a Base Model to test whether our manipulated condition variables improved the fit of the null model and found that Type, Strength, and Visual Field significantly improved the fit of the model to the data ($\chi^2 = 92.17, df = 4, p < .001$).

We next fit a Type and Strength Interaction Model, which improved the fit of the model over the Base model ($\chi^2 = 9.67, df = 3, p = .022$). The Type and Strength Interaction Model also fit significantly better than the Type model, which only included the condition variables and an interaction of Type and Visual Field ($\chi^2 = 8.95, df = 2, p = .011$). We then tested whether the Type and Strength Interaction Model would also fit better than the Strength Model, which only included the interaction of Strength and Visual Field. As the Strength Model did not significantly

Table 6
Mean percentage (with standard error and 95% confidence intervals) of relatedness endorsements and mean response time to make the relatedness judgement for each condition in each VF.

Type	VF	Strength	Relatedness Judgements (% Endorsed)			Response Time (ms)		
			Mean	SE	95% CI	Mean	SE	95% CI
Association	LVF	Strong	71.28	3.61	7.46	886.88	51.21	105.94
		Weak	57.13	4.1	8.48	977.85	56.02	115.88
		Unrelated	26.37	4.66	9.64	1112.94	71.77	148.47
	RVF	Strong	85.4	1.9	3.94	766.14	41.63	86.11
		Weak	68.64	2.73	5.66	971.33	64.65	133.74
		Unrelated	26.13	4.66	9.64	1127.14	67.1	138.8
Category	LVF	Strong	64.93	4.06	8.4	903.46	57.04	118.01
		Weak	46.28	4.44	9.19	992.09	57.57	119.1
		Unrelated	28.52	4.54	9.4	1039	114.01	235.85
	RVF	Strong	81.17	2.82	5.84	817	44.61	92.27
		Weak	55.16	4.8	9.93	883.96	105.52	218.29
		Unrelated	30.3	4.61	9.55	1193.92	71.66	148.23

Table 7

Mean N400 and LPC amplitudes (with standard errors and 95% confidence intervals) for each condition in each VF. N reflects the number of trials averaged after artifact rejection in each condition in each VF (N trials before artifact rejection: Association (696), Category (624)).

| Type | VF | Strength | N400 | | | | LPC | | | |
			N	μV	SE	95% CI	N	μV	SE	95% CI
Association	LVF	Strong	517	3.06	0.4	0.79	517	7.22	0.42	0.83
		Weak	527	1.84	0.41	0.8	561	4.42	0.39	0.77
		Unrelated	561	0.91	0.39	0.77	527	5.06	0.42	0.83
	RVF	Strong	479	4.74	0.44	0.86	479	9.34	0.42	0.83
		Weak	547	2.63	0.39	0.77	553	4.76	0.36	0.71
		Unrelated	553	0.82	0.4	0.78	547	7.09	0.41	0.81
Category	LVF	Strong	474	2.83	0.42	0.83	474	7.49	0.44	0.86
		Weak	491	1.19	0.43	0.84	464	4.88	0.43	0.84
		Unrelated	465	0.92	0.44	0.87	491	5.44	0.43	0.85
	RVF	Strong	459	4.28	0.43	0.84	459	9.28	0.42	0.82
		Weak	494	0.99	0.38	0.74	478	4.27	0.38	0.75
		Unrelated	493	1.05	0.41	0.8	494	6.16	0.4	0.79
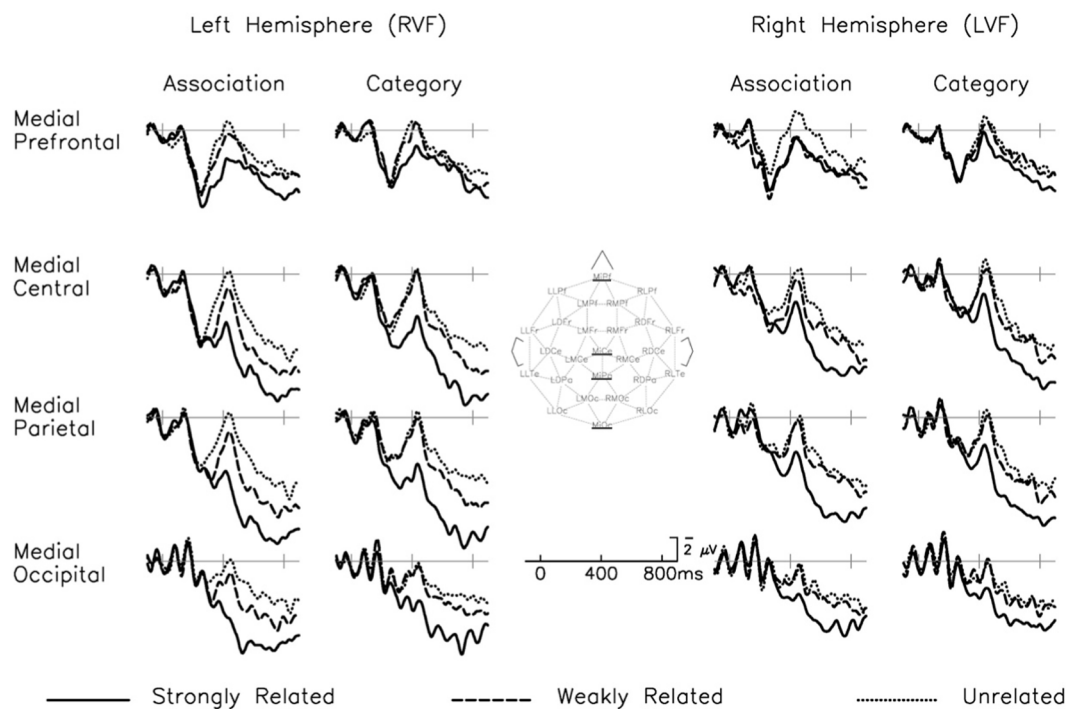
Fig. 3. Grand averages for each level of prime-target relatedness, condition, and Hemisphere/VF are plotted at the four medial electrode sites (underlined). On both the N400 (300–500 ms) and LPC (600–900 ms) across condition and VF, strongly related prime-target pairs were the most facilitated. Relative to Experiment 1, lateralizing the prime diminished priming for weakly related pairs in all comparisons but the Association condition in the LH/RVF.

Table 8

Model estimates of relatedness judgements and response times with 95% confidence intervals and p-values. The intercept reflects the mean at the reference levels of association, strong, and LVF. Predictor estimates reflect the difference between the reference level and the factor level in parenthesis.

| Predictors | Relatedness Judgements | | | Response Time (ms) | | |
	Estimates	95% CI	p	Estimates	95% CI	p
Intercept	71.33	64.89–77.78	<0.001	902.35	789.91–1014.79	<0.001
Type (Category)	−6.45	−12.90–−0.01	0.050	−14.37	−126.81–98.07	0.802
VF (RVF)	15.60	6.49–24.71	0.001	−115.83	−274.84–43.19	0.153
Strength (Unrelated)	4.45	−3.44–12.34	0.268	180.80	43.09–318.52	0.010
Strength (Weak)	−16.40	−24.29–−8.51	<0.001	89.80	−47.91–227.51	0.200
Type (Category): VF (RVF)	−0.84	−9.95–8.27	0.856	24.46	−134.55–183.48	0.762
VF (RVF): Strength (Unrelated)	−15.95	−27.11–−4.79	0.005	188.15	−6.60–382.91	0.058
VF (RVF): Strength (Weak)	−4.98	−16.14–6.17	0.380	46.27	−148.48–241.02	0.640
Observations	288			288		
R² / R² adjusted	0.222 / 0.203			0.113 / 0.091		

differ from the Type and Strength Interaction Model ($\chi^2 = 0.81$, $df = 1$, $p = .37$), the Strength Model was selected as having the most parsimonious and best fitting fixed effects structure.

We then tested whether random slopes for Type, Strength, and Visual Field were needed in random effects specification of the Strength Model. Models with random slopes of either Type or Strength failed to converge. However, a random slope of Visual Field improved the fit of the Strength Model to the data ($\chi^2 = 6.12$, $p = .03$).

Following these model comparisons, the most parsimonious and best fitting model as determined by deviance and AIC was the Strength Model that included a slope for Visual Field. Estimates of the fixed effects in this model showed that, as in Experiment 1, ERPs were overall more positive in the N400 time window with RVF than with LVF presentation. Mean amplitudes were facilitated to strongly related pairs compared to weakly related and unrelated pairs. Follow-up contrasts indicated that weakly related pairs and unrelated pairs did not differ in mean amplitude ($F(1, 1887.46) = 1.42$, $p = .23$). Finally, the interaction of Strength and Visual Field arose because the priming effect for strongly related pairs (i.e., the difference between strongly related and unrelated pairs) was larger with RVF than with LVF presentation. Priming effects for weakly related pairs (compared to unrelated) were not different as a function of visual field ($F(1, 5610.08) = 0.92$, $p = .34$). Thus, there was an RVF advantage for priming from strongly-related pairs (of both types). Fig. 4 shows the final model predicted estimates for Strength, Type, and Visual Field, and Table 9 reports the estimates of the fixed effects for the Strength Model with a slope for Visual Field as well as the Type and Strength Interaction Model.

3.2.4. Model results of the LPC

To test the same predictions on the LPC, we again fit a series of models with the same predictors and coding scheme. The ICC of the null model was 0.05. Fitting models in the same sequence as described in the N400 Model results, we found that the Base Model improved the model fit over the null model ($\chi^2 = 164.31$, $df = 4$, $p < .001$). The Type and Strength Interaction Model significantly improved model fit over the Base Model ($\chi^2 = 21.84$, $df = 3$, $p < .001$). To test if a model including only one of the interactions was a better fit to the data than the Type and Strength Interaction Model, we fit a Type Model and a Strength Model, but the Type and Strength Interaction Model fit the data better than both the Type Model ($\chi^2 = 17.56$, $df = 2$, $p < .001$) and the Strength Model ($\chi^2 = 4.62$, $df = 1$, $p = .032$).

We then tested if random slopes of Type, Strength, and/or Visual Field would improve the model fit of the Type and Strength Interaction Model. A model with a random slope of Strength did not converge and including a random slope for Type did not improve model fit ($\chi^2 = 3.64$, $p = .11$). However, including a random slope for Visual Field

significantly improved the fit of the Strength and Type Interaction Model ($\chi^2 = 18.06$, $p < .001$). Therefore, the Type and Strength Interaction Model with a random slope for Visual Field was chosen as the best fitting model based on the deviance tests and parsimony.

Similar to the N400 fixed effects estimates, stimuli in the RVF (compared to the LVF) elicited more positive amplitudes overall. In this time window, mean amplitudes did not differ overall for the categorically related pairs and associatively related pairs; however, associatively related pairs were more positive than categorically related pairs in the RVF. Strongly related pairs elicited more positive amplitudes than weakly related and unrelated pairs, but weakly related pairs were not significantly different from unrelated ones overall ($F(1, 1911.16) = 1.42$, $p = .23$). As in the N400 time window, the priming effect for strongly related pairs (compared to unrelated) was larger in the RVF/LH than in the LVF/RH. However, on the LPC, the difference between weakly related and strongly related pairs was not significantly different across visual field. Instead, weakly related pairs also showed more priming (compared to unrelated) in the RVF ($F(1, 5608.93) = 10.32$, $p = .001$). To summarize, in the LPC window, the RVF advantage for priming from strongly-related pairs seen on the N400 was maintained, and extended to weakly related primes as well. Fig. 4 shows the final LPC model predicted estimates of Type, Strength, and Visual Field, and the estimates of the fixed effects for the Type and Strength Interaction Model with a random slope for Visual Field are reported in Table 9.

3.3. Discussion experiment 2

Experiment 2 tested whether lateralizing the prime in addition to the target would reveal patterns of priming in each hemisphere consistent with either the Coarse Coding or the Association/Category hypotheses. However, as with Experiment 1, the result pattern did not support either account. Overall, lateralization of the prime reduced priming effects for weakly related pairs; however, there was still a graded pattern of facilitation on the N400 and LPC in both visual fields. Lateralization of the prime also produced a priming advantage for stimuli presented in the RVF/LH. On the N400, this advantage was limited to strongly related pairs (of both types), but, on the LPC, it extended to weakly related pairs. Behavioral judgements also revealed that participants were able to overtly report the relatedness of weak pairs better when presented to the RVF/LH. However, this pattern of visual field effects was not consistent with either the Coarse Coding or the Association/Category hypothesis.

There was no disadvantage for priming from weakly related pairs in the RVF/LH for either relationship type on any measure. Indeed, the pattern on the LPC and in behavioral judgments was opposite to that predicted by Coarse Coding, with an RVF/LH *advantage* for weakly-related pairs. Contrary to the Association/Category hypothesis, we
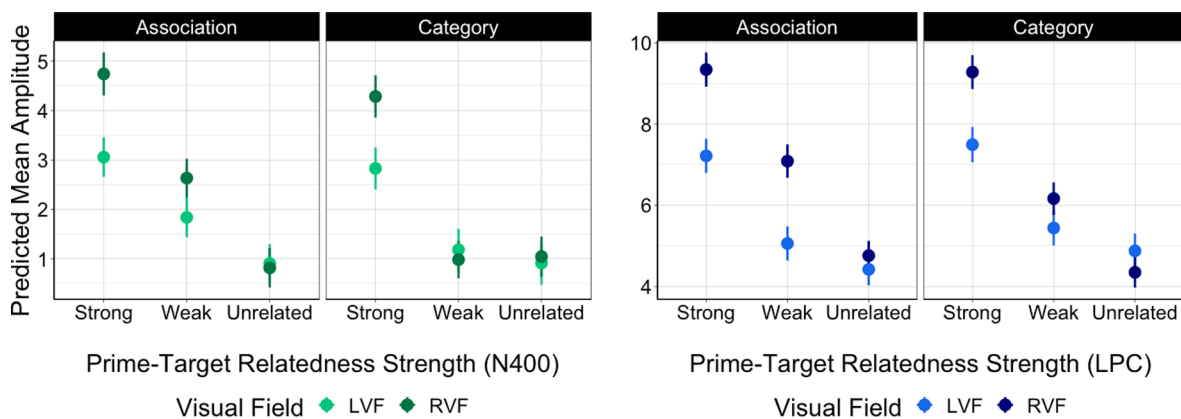
Fig. 4. Plotted are predicted mean amplitudes from the best fitting models of the N400 and LPC. For both the N400 and LPC and in each condition and VF, priming was greatest for strongly related prime-target pairs. For the N400 and LPC in the LH/RVF, especially in the Association condition, priming was graded by relatedness strength as in Experiment 1. Otherwise, lateralizing the prime reduced priming effects for weakly related prime-target pairs.

Table 9

Estimates of the fixed effects for the best fitting models for the N400 and LPC, as well as the Type and Strength Interaction Model for comparison on the N400. Under each estimate, 95% confidence intervals are reported in square brackets and standard errors are reported in parentheses. Association (Type), Strong (Strength) and LVF (Visual Field) were coded as reference levels, and for each predictor, the level in parentheses indicates what factor level is being compared to the reference.

Predictors	Strength Model (N400) Estimates	t	Type and Strength Model (N400) Estimates	t	Type and Strength Model with VF Slope (LPC) Estimates	t
(Intercept)	3.25 *** [1.92–4.58] (0.68)	4.79	3.14 *** [1.86–4.42] (0.65)	4.80	7.02 *** [5.42–8.63] (0.82)	8.57
Visual Field (Right)	1.51 *** [0.63–2.39] (0.45)	3.38	1.74 *** [0.85–2.62] (0.45)	3.84	2.44 *** [1.43–3.44] (0.51)	4.75
Strength (Unrelated)	−2.05 *** [−2.86–−1.24] (0.41)	−4.95	−2.03 *** [−2.85–−1.22] (0.41)	−4.91	−2.64 *** [−3.43–−1.86] (0.40)	−6.60
Strength (Weak)	−1.56 *** [−2.37–−0.75] (0.41)	−3.77	−1.54 *** [−2.36–−0.73] (0.41)	−3.72	−2.17 *** [−2.95–−1.38] (0.40)	−5.41
Type (Category)	−0.46 [−0.96–0.03] (0.25)	−1.84	−0.26 [−0.93–0.40] (0.34)	−0.78	0.46 [−0.18–1.10] (0.33)	1.40
Visual Field (Right): Strength (Unrelated)	−1.59 ** [−2.67–−0.51] (0.55)	−2.88	−1.62 ** [−2.70–−0.54] (0.55)	−2.94	−2.16 *** [−3.21–−1.10] (0.54)	−4.00
Visual Field (Right): Strength (Weak)	−1.07 [−2.15–0.01] (0.55)	−1.93	−1.10 * [−2.18–−0.02] (0.55)	−1.99	−0.45 [−1.51–0.61] (0.54)	−0.84
Visual Field (Right): Type (Category)			−0.40 [−1.28–0.48] (0.45)	−0.90	−0.94 * [−1.80–−0.08] (0.44)	−2.14

* p < 0.05 ** p < 0.01 *** p < 0.001

found, as in Experiment 1, that priming for both types of relationship was obtained in both visual fields. There was no advantage for category priming in the LVF/RH on any measure; instead, it was the RVF/LH that showed greater priming effects for strongly related category pairs on both the N400 and the LPC. Moreover, there was no indication that priming effects in the RVF/LH were larger for associatively related than categorically related pairs.

Thus, as in Experiment 1, priming patterns were overall quite similar across the visual field conditions, albeit stronger with RVF presentation. As it has been shown that lateralization disadvantages word recognition, especially for stimuli presented in the LVF (e.g., Jordan et al., 1998, Jordan et al., 2000; Jordan and Patching, 2003, Jordan et al., 2003; Jordan & Patching, 2006; Patching & Jordan, 1998), this may account for the smaller priming effects in the LVF and lower behavioral endorsement of relatedness for LVF compared to RVF pairs. Increased difficulty with word recognition, and concomitant increases in task difficulty for making an explicit similarity judgment, may also explain the general reduction of priming for weakly related pairs on both the N400 and LPC in Experiment 2.

4. General discussion

The goal of the present study was to test both the Coarse Coding and Association/Category theories of semantic processing asymmetries, using a task designed to promote explicit appreciation of semantic relationships and measuring ERPs to assess both automatic and controlled aspects of semantic processing. The Coarse Coding hypothesis proposes that the RH/LVF coarsely codes information and activates even meaning features that are indirectly related to the context, whereas the LH/RVF narrowly focuses on the meaning most relevant to the context (Beeman,

1998; Jung-Beeman, 2005). The Association/Category hypothesis predicts that the LH is a localist network that should primarily or exclusively apprehend associative relatedness, whereas the RH is a distributed network and should therefore primarily or exclusively apprehend categorical relatedness (Deacon et al., 2004; Grose-Fifer & Deacon, 2004). However, in two experiments, using first central and then lateral prime presentation, the current study did not find support for either theory. Rather, both hemispheres showed priming for both types of relation (association, category) and manifested a graded sensitivity to relatedness strength (strongly related, weakly related, unrelated), on both the N400 and the LPC and in behavior.

Using the N400 as a dependent measure allows a strong test of the Coarse Coding and Association/Category hypotheses, as it taps into the initial aspects of semantic access that are the focus of both accounts (see review by Kutas & Federmeier, 2011). The result pattern was clear: Early aspects of semantic processing unfold similarly in both cerebral hemispheres, allowing both to appreciate associative and categorical semantic relationships in a manner that is similarly graded by strength. Priming for strongly related pairs was ubiquitously present in both visual fields in both experiments for both types of relations, and, with central prime presentation, was similarly graded in the two visual fields. When the prime was also lateralized, priming for strongly related items of both types was more robust for RVF/LH than LVF/RH presentation and priming for weakly related items was reduced overall. However, contrary to the predictions of the Association/Category hypotheses, there was no evidence in either experiment for an RVF/LH bias to process relationships based on association nor for an LVF/RH bias to process relationships based on shared category. With respect to the Coarse Coding hypothesis, there was also no evidence – not even a numerical pattern – suggesting stronger priming in weakly related pairs for

presentation biased toward the RH.

The patterns observed in the present experiment accord with our predictions based on prior ERP work by Kandhadai & Federmeier (2008, 2010a,b). The series of experiments reported in that work used multiple kinds of tasks (passive reading, lexical decision, and semantic relatedness judgments) and multiple kinds of stimuli (ambiguous and unambiguous summation primes, as well as forward, backward, and symmetrically associated word pairs). In all cases, the hemispheres showed identical priming patterns on the N400. Both hemispheres showed priming for all relationship types tested, and, moreover, in all cases the hemispheres were similarly sensitive to manipulations of relationship strength; in particular, there was no evidence that the RH was better able to appreciate weak or backward associations or to summate priming across multiple words. The current study was the first to separate categorical and associative relationships and to examine priming when both prime and target were lateralized. Taken together with the prior studies, the accumulated evidence strongly refutes claims that the hemispheres differ in how they represent or initially process semantic information.

Although both the Coarse Coding and the Association/Category hypothesis are centered on representational differences that should manifest on semantic access, we also examined response patterns on the LPC. Because the LPC has been linked to more explicit aspects of processing (e.g., Olichney et al., 2000, Swaab et al., 1998, Van Petten and Kutas, 1991), this allows a test of whether controlled semantic processing might show biases that align with these accounts. In fact, prior work has observed asymmetries on the LPC under some task conditions, with the LH showing stronger LPC priming for backward associations under passive (although not under active) task conditions (Kandhadai & Federmeier, 2010a,b). Again, however, the predictions of the Coarse Coding and Association/Category hypotheses were not supported by the LPC result patterns. As for the N400, with central prime presentation, priming patterns were indistinguishable across visual field in this time window, and, with lateralized prime presentation, favored the RVF/LH not only for strongly but also for weakly related pairs – thus, opposite to the predictions of the Coarse Coding hypothesis. Instead, when task conditions are difficult, it seems that the LH may be better at using strategic semantic processing to integrate weak semantic relations, supporting the task demands of overtly reporting those relationships, as seen in participants' judgement behavior (cf. Kandhadai & Federmeier, 2010a,b).

In the current work, we prioritized testing the abilities of the hemispheres when the task demands that semantic relationships be explicitly processed, and we found little difference. However, the past literature has shown that a key source of asymmetric processing patterns may be what happens when controlled processing is not necessary for the task, with the LH more likely to engage active strategies. For example, the literature looking at hemispheric asymmetries during sentence processing has uncovered robust, replicable differences wherein the LH, but not the RH, engages in active prediction (e.g., Federmeier & Kutas, 1999; Wlotko & Federmeier, 2013; see review in Federmeier, 2007). Similar patterns suggesting prediction by the LH but not the RH have also been attested for processing in short phrases and word pairs (Kandhadai & Federmeier, 2010b; Huang et al., 2010). Predictive processes in the LH can take advantage of higher-level context information to prepare for likely upcoming information. For example, when presented with sentences that have strong contextual constraint, the LH is able set attention and prepare not only for the likely conceptual properties of upcoming words, but also perceptual properties (e.g., Wlotko & Federmeier, 2007; Huang et al. 2010, Kandhadai & Federmeier, 2010a). Predictive processing in the LH also can bring additional information online (Federmeier & Kutas, 1999) and can augment effects of context, especially when context information is only moderate or weak (Wlotko & Federmeier, 2013; Kandhadai & Federmeier, 2010b) – similar to the LPC and behavioral patterns seen here in Experiment 2. Thus, rather than asserting that patterns of asymmetry that have sometimes been

observed in, e.g., behavioral priming tasks are due to fundamental representational differences, it might be more fruitful to consider the possibility that asymmetries are more likely to be due, instead, to differing strategies for using similar semantic representations to meet task goals.

5. Conclusion

Taken together, the evidence across a breadth of work investigating semantics and language comprehension in the cerebral hemispheres suggests that the hemispheres may not fundamentally differ in the way in which meaning is organized and represented – the hemispheres *can* process information similarly when conditions are right – but rather in the way in which meaning is recruited given the demands of the task on the system. Task matters, as evidence suggests that the semantic system can flexibly activate the relevant knowledge to fit the current task demands. For example, Willits, Amato, and MacDonald (2015) hypothesized that people efficiently recruit knowledge learned from interacting with the world or knowledge gleaned from language experience depending on the degree to which it is relevant for the task at hand. Across four experiments utilizing exactly the same stimuli, they demonstrated that world knowledge was most predictive of behavior in tasks that required world knowledge and conversely, that language knowledge most related to performance on language tasks. They concluded that task demands can alter the way in which people rely on prior experiences in the world and with language (Willits, Amato, and MacDonald, 2015). Accordingly, rather than reveal the representational structure of each hemisphere, one possibility is that task and context can shape the way each hemisphere utilizes semantic information in service of the task goal (e.g, Kandhadai & Federmeier, 2010; Willits, Amato, & MacDonald, 2015).

Taking task demands into account provides a different lens by which to view the breadth of conflicting findings in the literature on priming in the two cerebral hemispheres. Rather than seeking the task or stimulus manipulations that will probe the "true" underlying nature of semantic representations in each hemisphere, attending to how processing differs under different task conditions may *reveal* how each of the hemispheres is able to warp their representational space and dynamically adapt to the task at hand. A system that is able to flexibly adapt across the varied contexts and demands it encounters would be better suited to comprehend meaning than a system that is optimized for a single process – and a system that can do this in multiple ways in parallel, distributed across the two cerebral hemispheres, is even more adaptable.

CRediT authorship contribution statement

Emily N. Mech: Formal analysis, Visualization, Data curation, Writing – original draft. **Padmapriya Kandhadai:** Conceptualization, Methodology, Software, Investigation, Writing – review & editing. **Kara D. Federmeier:** Conceptualization, Resources, Supervision, Validation, Project administration, Funding acquisition, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Appendix A

Experiment 1: Central Prime
Left Visual Field/Right Hemisphere – Association Condition
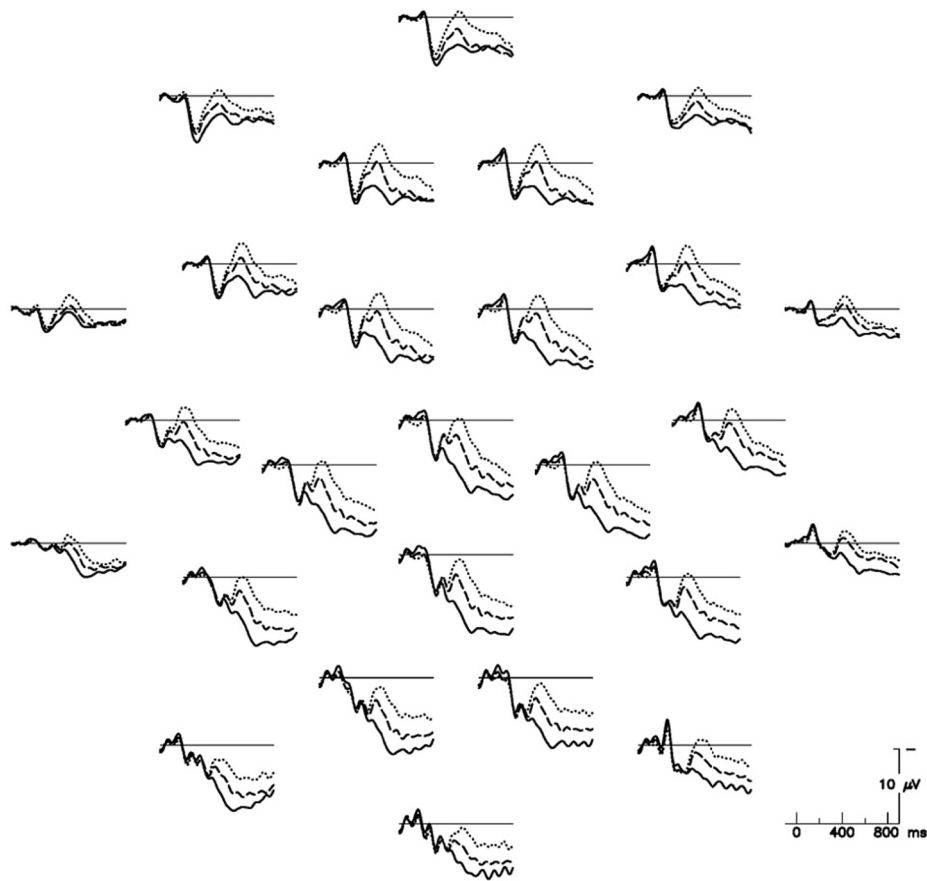
——— Strongly Related

------- Weakly Related

··········· Unrelated

Right Visual Field/Left Hemisphere – Association Condition
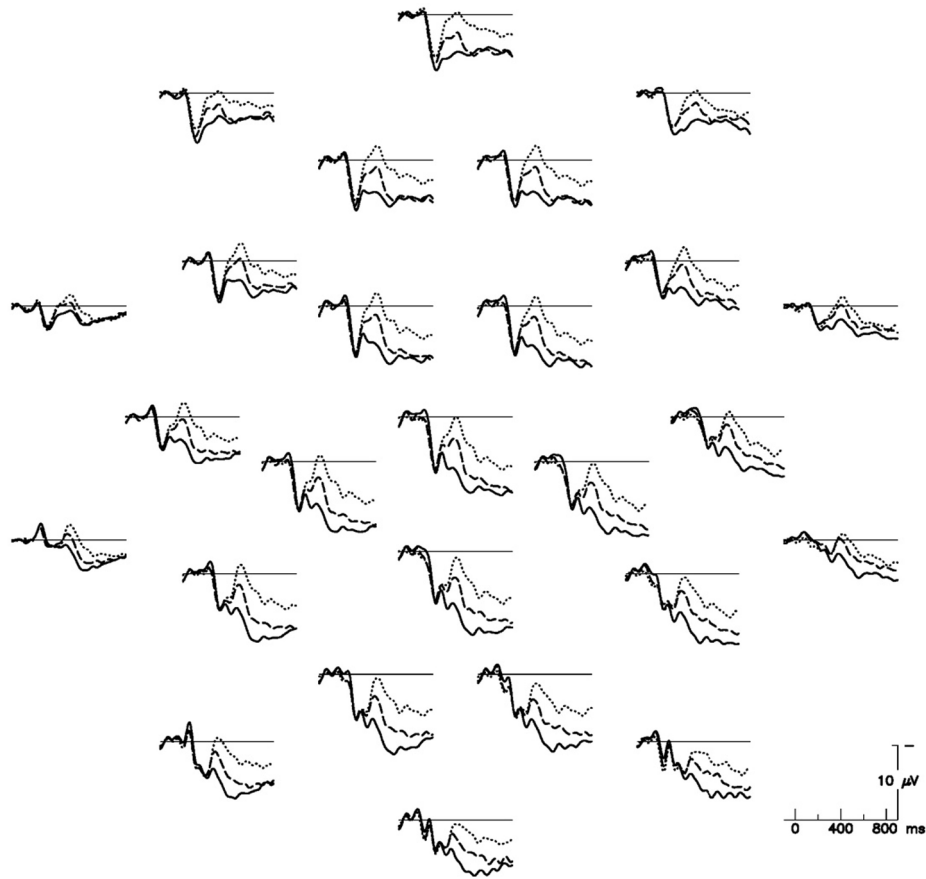
——— Strongly Related

------- Weakly Related

·············· Unrelated

Left Visual Field/Right Hemisphere – Category Condition
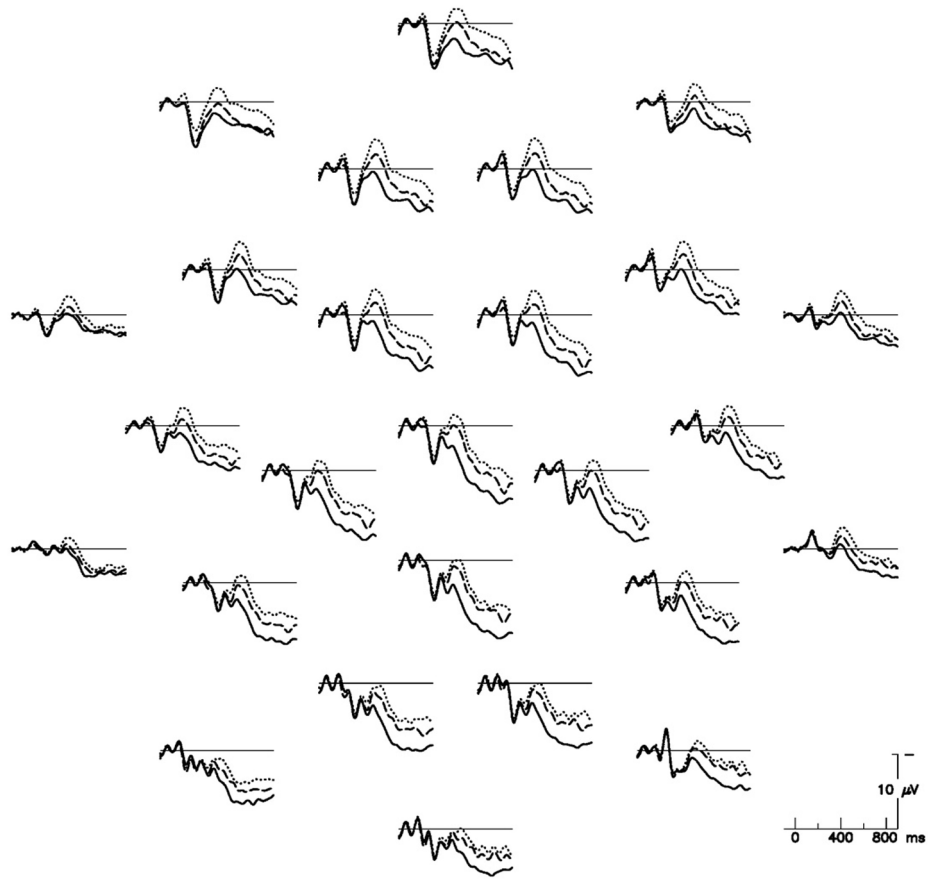
——— Strongly Related

------- Weakly Related

·················· Unrelated

Right Visual Field/Left Hemisphere – Category Condition
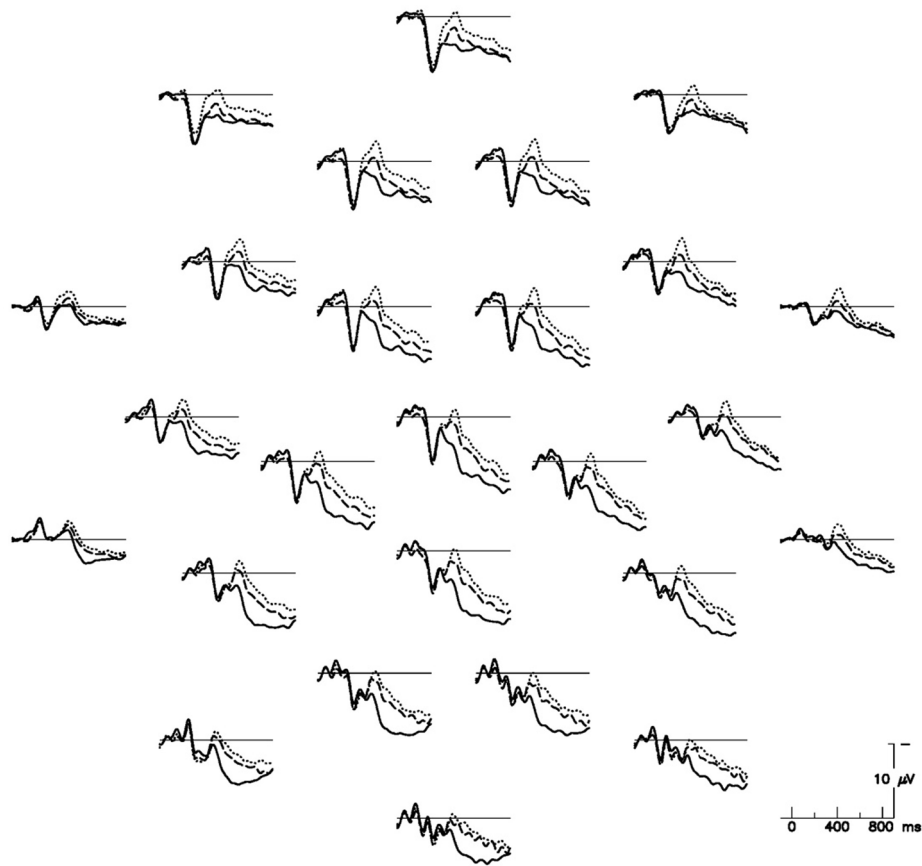
——— Strongly Related

------- Weakly Related

.... Unrelated

Experiment 2: Lateral Prime
Left Visual Field/Right Hemisphere – Association Condition
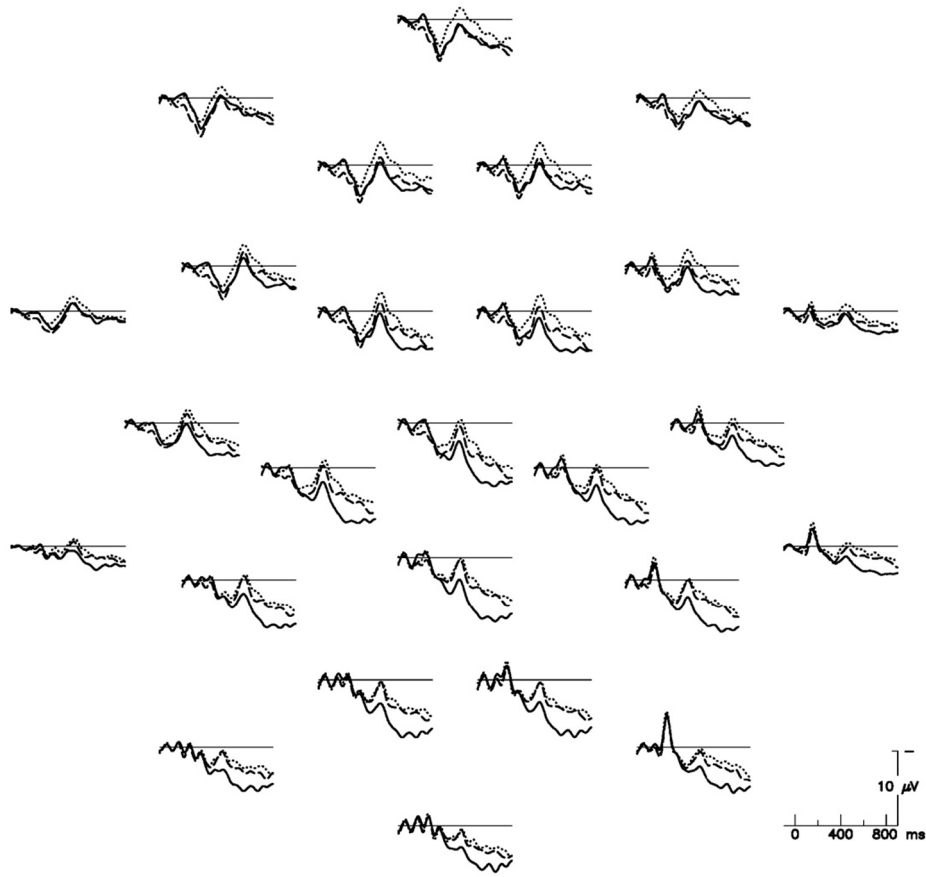
——— Strongly Related

------- Weakly Related

·············· Unrelated

Right Visual Field/Left Hemisphere – Association Condition

——— Strongly Related

------- Weakly Related

·············· Unrelated

Left Visual Field/Right Hemisphere – Category Condition
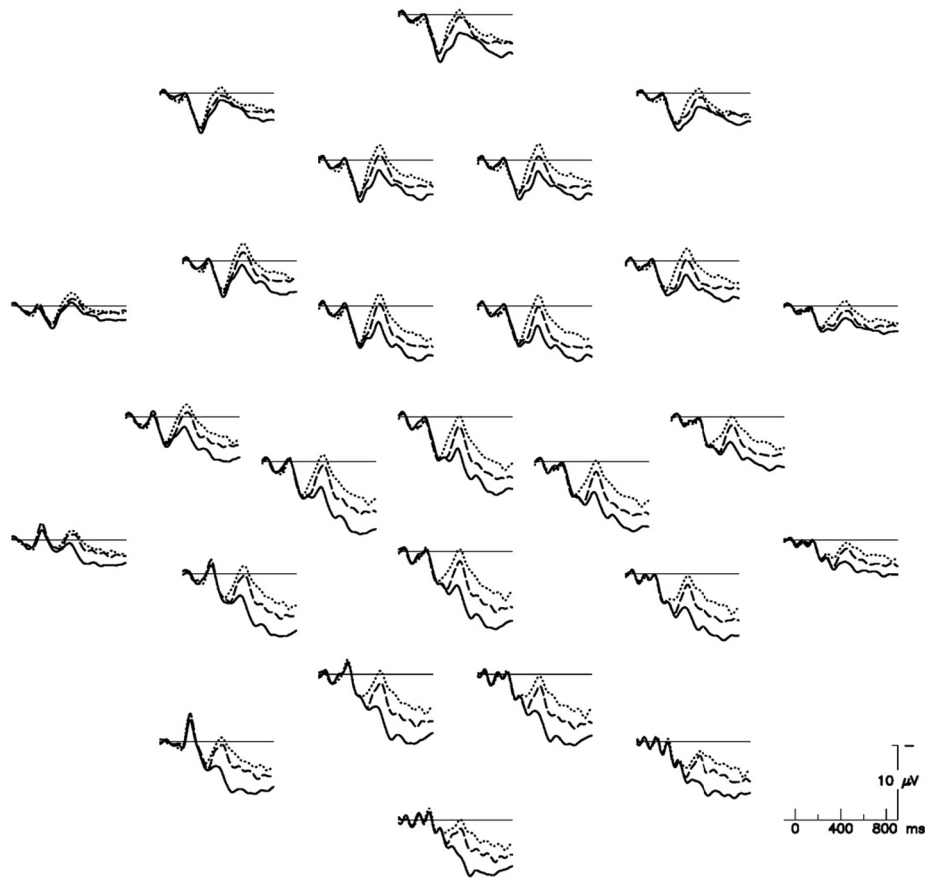
——— Strongly Related

------- Weakly Related

·········· Unrelated

Right Visual Field/Left Hemisphere – Category Condition

——— *Strongly Related*

------- *Weakly Related*

············· *Unrelated*
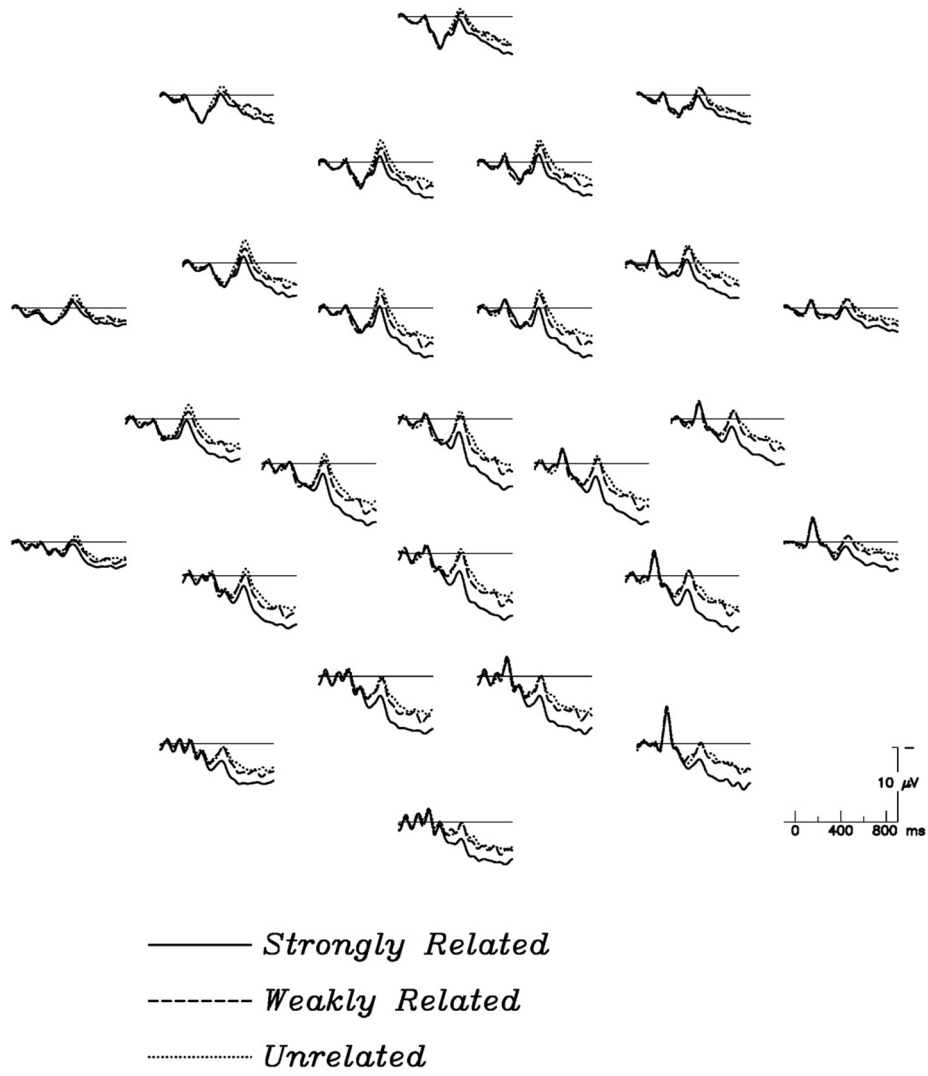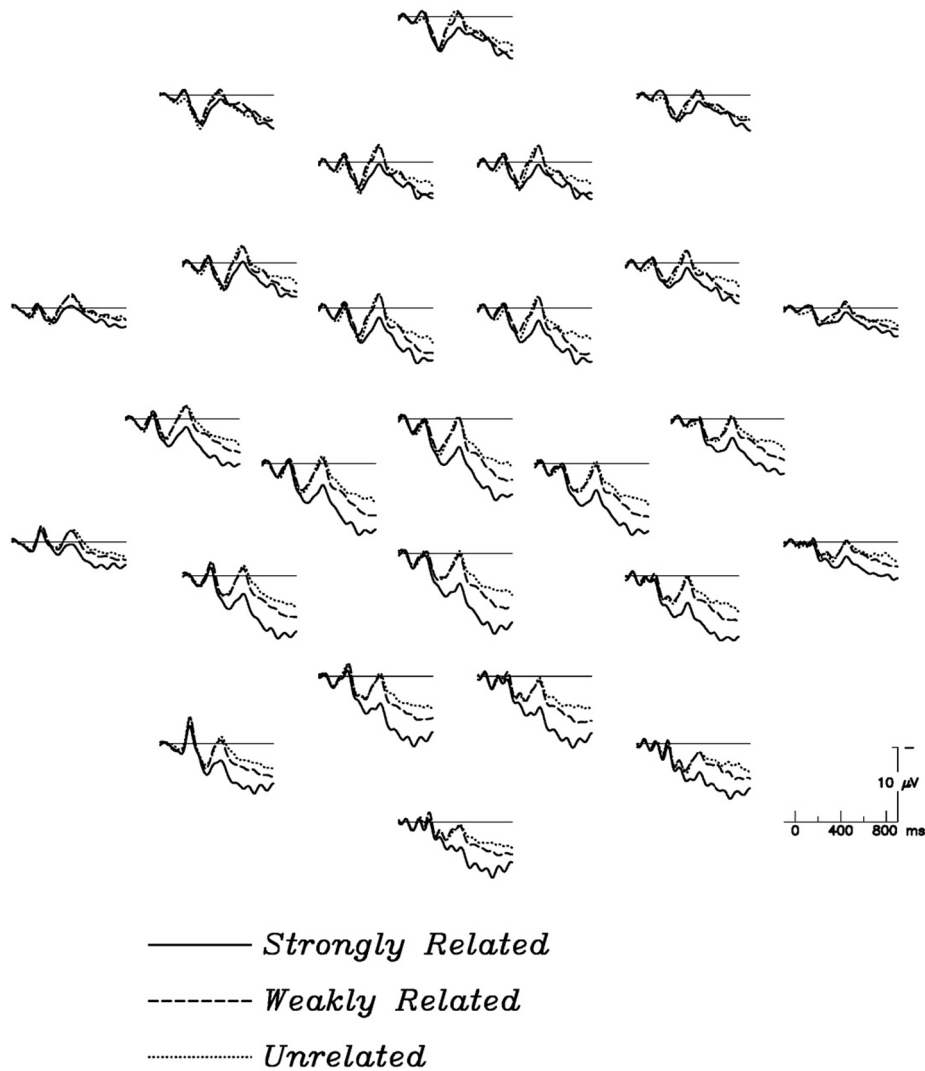
Appendix B

Experiment 1: Central Prime
N400 Model Comparisons

| Predictors	Base Model		Strength Model		Type Model		Strength and Type Interaction Model	
	Estimates	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*
(Intercept)	5.87 ***	8.79	5.88 ***	8.57	5.83 ***	8.63	5.84 ***	8.42
	[4.56–7.18]		[4.54–7.23]		[4.51–7.16]		[4.48–7.20]	
	(0.67)		(0.69)		(0.68)		(0.69)	
Visual Field (Right)	0.81 ***	3.71	0.79 *	2.07	0.89 **	2.96	0.87 *	2.01
	[0.38–1.23]		[0.04–1.53]		[0.30–1.48]		[0.02–1.72]	
	(0.22)		(0.38)		(0.30)		(0.43)	
Strength (Unrelated)	−4.72 ***	−13.01	−4.70 ***	−10.45	−4.72 ***	−13.01	−4.70 ***	−10.45
	[−5.43−−4.01]		[−5.58−−3.82]		[−5.43−−4.01]		[−5.58−−3.82]	
	(0.36)		(0.45)		(0.36)		(0.45)	
Strength (Weak)	−2.88 ***	−7.95	−2.93 ***	−6.51	−2.88 ***	−7.96	−2.93 ***	−6.51
	[−3.59−−2.17]		[−3.81−−2.05]		[−3.59−−2.17]		[−3.81−−2.05]	
	(0.36)		(0.45)		(0.36)		(0.45)	

(*continued*)

Predictors	Base Model		Strength Model		Type Model		Strength and Type Interaction Model	
	Estimates	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*
Type (Category)	−1.83 ***	−6.19	−1.83 ***	−6.18	−1.74 ***	−4.75	−1.74 ***	−4.75
	[−2.41−−1.25] (0.30)		[−2.41−−1.25] (0.30)		[−2.46−−1.02] (0.37)		[−2.46−−1.03] (0.37)	
VFRVF:strengthUnrel			−0.04	−0.07			−0.04	−0.07
			[−1.09−1.01] (0.53)				[−1.08−1.01] (0.53)	
VFRVF:strengthWeak			0.10	0.19			0.10	0.19
			[−0.94−1.14] (0.53)				[−0.94−1.14] (0.53)	
VFRVF:typeCAT					−0.17	−0.40	−0.17	−0.39
					[−1.02−0.68] (0.43)		[−1.02−0.68] (0.43)	
Random Effects								
σ^2	74.83		74.83		74.83		74.83	
τ_{00}	3.35 item		3.35 item		3.35 item		3.35 item	
	8.37 participant		8.37 participant		8.37 participant		8.37 participant	
N	24 participant		24 participant		24 participant		24 participant	
	333 item		333 item		333 item		333 item	
Observations	6400		6400		6400		6400	
Marginal R^2 / Conditional R^2	0.052 / 0.180		0.052 / 0.180		0.052 / 0.180		0.052 / 0.180	
AIC	46083.221		46087.148		46085.064		46088.992	
log-Likelihood	−23033.611		−23033.574		−23033.532		−23033.496	

* p < 0.05 ** p < 0.01 *** p < 0.001

LPC Model Comparisons

Predictors	Base Model		Base Model with Strength Slope		Strength Model		Type Model		Type and Strength Interaction Model	
	Estimates	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*
(Intercept)	9.60 ***	10.94	9.59 ***	10.20	9.74 ***	10.93	9.56 ***	10.82	9.70 ***	10.81
	[7.88–11.32] (0.88)		[7.74–11.43] (0.94)		[7.99–11.49] (0.89)		[7.83–11.29] (0.88)		[7.94–11.46] (0.90)	
Visual Field (Right)	0.21	0.94	0.21	0.99	−0.08	−0.20	0.29	0.95	0.00	0.01
	[−0.22–0.63] (0.22)		[−0.21–0.64] (0.22)		[−0.82–0.67] (0.38)		[−0.31–0.88] (0.30)		[−0.85–0.86] (0.43)	
Strength (Unrelated)	−3.93 ***	−12.02	−3.88 ***	−6.73	−4.12 ***	−9.76	−3.93 ***	−12.02	−4.12 ***	−9.76
	[−4.57−−3.29] (0.33)		[−5.01−−2.75] (0.58)		[−4.95−−3.29] (0.42)		[−4.57−−3.29] (0.33)		[−4.95−−3.29] (0.42)	
Strength (Weak)	−1.97 ***	−6.05	−1.96 ***	−4.86	−2.20 ***	−5.21	−1.98 ***	−6.05	−2.20 ***	−5.21
	[−2.61−−1.34] (0.33)		[−2.75−−1.17] (0.40)		[−3.03−−1.37] (0.42)		[−2.62−−1.34] (0.33)		[−3.03−−1.37] (0.42)	
Type (Category)	−0.69 *	−2.57	−0.70 **	−2.62	−0.68 *	−2.57	−0.60	−1.75	−0.60	−1.74
	[−1.21−−0.16] (0.27)		[−1.22−−0.18] (0.27)		[−1.21−−0.16] (0.27)		[−1.28−0.07] (0.34)		[−1.28−0.08] (0.34)	
Visual Field (Right): Strength (Unrelated)					0.38	0.71			0.38	0.71
					[−0.67–1.43] (0.54)				[−0.67–1.44] (0.54)	
Visual Field (Right): Strength (Weak)					0.45	0.85			0.45	0.85
					[−0.60–1.50] (0.54)				[−0.60–1.50] (0.54)	
Visual Field (Right): Type (Category)							−0.17	−0.38	−0.17	−0.38
							[−1.02−0.69] (0.44)		[−1.02−0.69] (0.44)	
Random Effects										
σ^2	75.86		74.88		75.86		75.86		75.86	
τ_{00}	1.93 item		1.99 item		1.93 item		1.93 item		1.93 item	
	16.53 participant		19.19 participant		16.52 participant		16.53 participant		16.52 participant	
τ_{11}			5.40 participant.strengthUnrel							
			1.33 participant.strengthWeak							
ρ_{01}			−0.33 participant.strengthUnrel							
			−0.48 participant.strengthWeak							

(*continued*)

Predictors	Base Model		Base Model with Strength Slope		Strength Model		Type Model		Type and Strength Interaction Model	
	Estimates	t	Estimates	t	Estimates	t	Estimates	t	Estimates	t
N	24 participant		24 participant		24 participant		24 participant		24 participant	
	333 item		333 item		333 item		333 item		333 item	
Observations	6400		6400		6400		6400		6400	
Marginal R^2 / Conditional R^2	0.028 / 0.218		0.027 / 0.229		0.028 / 0.218		0.028 / 0.218		0.028 / 0.218	
AIC	46113.446		46081.334		46116.622		46115.300		46118.476	
log-Likelihood	−23048.723		−23027.667		−23048.311		−23048.650		−23048.238	

* p < 0.05 ** p < 0.01 *** p < 0.001

Experiment 2: Lateral Prime
 N400 Model Comparisons

Predictors	Base Model		Strength Model		Strength Model with VF Slope		Type Model		Type and Strength Interaction Model	
	Estimates	t	Estimates	t	Estimates	t	Estimates	t	Estimates	t
(Intercept)	3.69 ***	5.90	3.24 ***	5.02	3.25 ***	4.79	3.60 ***	5.68	3.14 ***	4.80
	[2.46–4.91]		[1.97–4.50]		[1.92–4.58]		[2.36–4.84]		[1.86–4.42]	
	(0.63)		(0.65)		(0.68)		(0.63)		(0.65)	
Visual Field (Right)	0.62 **	2.75	1.54 ***	3.88	1.51 ***	3.38	0.80 **	2.58	1.74 ***	3.84
	[0.18–1.05]		[0.76–2.32]		[0.63–2.39]		[0.19–1.40]		[0.85–2.62]	
	(0.22)		(0.40)		(0.45)		(0.31)		(0.45)	
Strength (Unrelated)	−2.84 ***	−9.10	−2.04 ***	−4.92	−2.05 ***	−4.95	−2.84 ***	−9.10	−2.03 ***	−4.91
	[−3.45−−2.23]		[−2.85−−1.23]		[−2.86−−1.24]		[−3.45−−2.23]		[−2.85−−1.22]	
	(0.31)		(0.41)		(0.41)		(0.31)		(0.41)	
Strength (Weak)	−2.08 ***	−6.67	−1.54 ***	−3.72	−1.56 ***	−3.77	−2.08 ***	−6.67	−1.54 ***	−3.72
	[−2.69−−1.47]		[−2.36−−0.73]		[−2.37−−0.75]		[−2.69−−1.47]		[−2.36−−0.73]	
	(0.31)		(0.41)		(0.41)		(0.31)		(0.41)	
Type (Category)	−0.47	−1.84	−0.47	−1.84	−0.46	−1.84	−0.28	−0.82	−0.26	−0.78
	[−0.96–0.03]		[−0.96–0.03]		[−0.96–0.03]		[−0.94–0.39]		[−0.93–0.40]	
	(0.25)		(0.25)		(0.25)		(0.34)		(0.34)	
Visual Field (Right): Strength (Unrelated)			−1.61 **	−2.93	−1.59 **	−2.88			−1.62 **	−2.94
			[−2.69−−0.53]		[−2.67−−0.51]				[−2.70−−0.54]	
			(0.55)		(0.55)				(0.55)	
Visual Field (Right): Strength (Weak)			−1.10 *	−1.99	−1.07	−1.93			−1.10 *	−1.99
			[−2.18−−0.01]		[−2.15–0.01]				[−2.18−−0.02]	
			(0.55)		(0.55)				(0.55)	
Visual Field (Right): Type (Category)							−0.38	−0.85	−0.40	−0.90
							[−1.26–0.50]		[−1.28–0.48]	
							(0.45)		(0.45)	
Random Effects										
σ^2	75.47		75.35		75.13		75.46		75.34	
τ_{00}	2.27 item		2.29 item		2.25 item		2.27 item		2.29 item	
	7.53 participant		7.53 participant		8.60 participant		7.53 participant		7.54 participant	
τ_{11}					1.00 participant.VFRVF					
ρ_{01}					−0.44 participant					
N	24 participant		24 participant		24 participant		24 participant		24 participant	
	660 item		660 item		660 item		660 item		660 item	
Observations	6059		6059		6059		6059		6059	
Marginal R^2 / Conditional R^2	0.018 / 0.131		0.019 / 0.132		0.019 / 0.135		0.018 / 0.131		0.019 / 0.132	
AIC	43646.199		43641.340		43639.223		43647.478		43642.532	
log-Likelihood	−21815.099		−21810.670		−21807.611		−21814.739		−21810.266	

* p < 0.05 ** p < 0.01 *** p < 0.001

LPC Model Comparisons

Predictors	Base Model		Strength Model		Type Model		Type and Strength Interaction Model		Type and Strength Interaction Model with VF Slope	
	Estimates	t	Estimates	t	Estimates	t	Estimates	t	Estimates	t
(Intercept)	7.69 ***	10.72	7.26 ***	9.89	7.47 ***	10.31	7.03 ***	9.48	7.02 ***	8.57

(continued)

Predictors	Base Model Estimates	t	Strength Model Estimates	t	Type Model Estimates	t	Type and Strength Interaction Model Estimates	t	Type and Strength Interaction Model with VF Slope Estimates	t
Visual Field (Right)	[6.28–9.09] (0.72) 1.09 ***	4.95	[5.82–8.70] (0.73) 1.96 ***	5.04	[6.05–8.89] (0.72) 1.52 ***	5.02	[5.58–8.49] (0.74) 2.42 ***	5.45	[5.42–8.63] (0.82) 2.44 ***	4.75
Strength (Unrelated)	[0.66–1.52] (0.22) −3.72 ***	−12.44	[1.20–2.72] (0.39) −2.67 ***	−6.65	[0.93–2.12] (0.30) −3.72 ***	−12.44	[1.55–3.29] (0.44) −2.66 ***	−6.62	[1.43–3.44] (0.51) −2.64 ***	−6.60
Strength (Weak)	[−4.31−−3.13] (0.30) −2.37 ***	−7.93	[−3.46−−1.88] (0.40) −2.16 ***	−5.38	[−4.30−−3.13] (0.30) −2.37 ***	−7.94	[−3.44−−1.87] (0.40) −2.17 ***	−5.39	[−3.43−−1.86] (0.40) −2.17 ***	−5.41
Type (Category)	[−2.96−−1.78] (0.30) −0.02	−0.10	[−2.95−−1.38] (0.40) −0.02	−0.07	[−2.96−−1.79] (0.30) 0.43	1.31	[−2.95−−1.38] (0.40) 0.45	1.39	[−2.95−−1.38] (0.40) 0.46	1.40
Visual Field (Right): Strength (Unrelated)	[−0.50–0.45] (0.24)		[−0.49–0.46] (0.24) −2.11 *** [−3.17−−1.05] (0.54)	−3.91	[−0.21–1.07] (0.33)		[−0.19–1.10] (0.33) −2.13 *** [−3.19−−1.07] (0.54)	−3.95	[−0.18–1.10] (0.33) −2.16 *** [−3.21−−1.10] (0.54)	−4.00
Visual Field (Right): Strength (Weak)			−0.44 [−1.50–0.62] (0.54)	−0.81			−0.44 [−1.51–0.62] (0.54)	−0.82	−0.45 [−1.51−0.61] (0.54)	−0.84
Visual Field (Right): Type (Category)					−0.91 * [−1.77−−0.05] (0.44)	−2.07	−0.94 * [−1.81−−0.08] (0.44)	−2.15	−0.94 * [−1.80−−0.08] (0.44)	−2.14
Random Effects										
σ^2	72.83		72.57		72.77		72.51		72.12	
τ_{00}	1.72 item 10.62 participant		1.78 item 10.64 participant		1.73 item 10.63 participant		1.79 item 10.65 participant		1.77 item 13.54 participant	
τ_{11}									1.58 participant.VFRVF	
ρ_{01}									−0.71 participant	
N	24 participant 660 item		24 participant 660 item		24 participant 660 item		24 participant 660 item		24 participant 660 item	
Observations	6059		6059		6059		6059		6059	
Marginal R^2 / Conditional R^2	0.030 / 0.170		0.032 / 0.173		0.030 / 0.171		0.033 / 0.174		0.033 / 0.179	
AIC	43407.891		43394.671		43405.611		43392.049		43377.987	
log-Likelihood	−21695.946		−21687.335		−21693.805		−21685.024		−21675.993	

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$

Appendix C

Experiment 1: Central Prime
ANOVA Results, N400 (Type: Category)

Predictor	df_{Num}	df_{Den}	Epsilon	F	p	η_g^2
VF	1.00	23.00		4.02	0.057	0.01
strength	1.54	35.50	0.77	42.63	0.000	0.18
strength × VF	1.80	41.36	0.90	0.07	0.912	0.00

Bayes Factor favoring interaction model over main effects model: $0.12 \pm 2.32\%$.
ANOVA Results, N400 (Type: Association).

Predictor	df_{Num}	df_{Den}	Epsilon	F	p	η_g^2
VF	1.00	23.00		7.63	0.011	0.02
strength	1.48	34.08	0.74	71.65	0.000	0.33
strength × VF	1.83	42.18	0.92	0.20	0.803	0.00

Bayes Factor favoring interaction model over main effects model: $0.12 \pm 2.26\%$.
ANOVA Results, LPC (Type: Category)

Predictor	df_{Num}	df_{Den}	Epsilon	F	p	η_g^2
VF	1.00	23.00		0.03	0.864	0.00
strength	1.54	35.31	0.77	25.08	0.000	0.09
strength × VF	1.94	44.53	0.97	0.64	0.528	0.00

Bayes Factor favoring interaction model over main effects model: 0.12 ± 2.55%.

ANOVA Results, LPC (Type: Association)

Predictor	df_{Num}	df_{Den}	Epsilon	F	p	η_g^2
VF	1.00	23.00		1.19	0.286	0.00
strength	1.71	39.29	0.85	38.08	0.000	0.15
strength × VF	1.85	42.64	0.93	0.37	0.677	0.00

Bayes Factor favoring interaction model over main effects model: 0.12 ± 2.01%.

Note. df_{Num} indicates degrees of freedom numerator. df^{Den} indicates degrees of freedom denominator. Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom, *p*-values and degrees of freedom in the table incorporate this correction. η_g^2 indicates generalized eta-squared. Electrode was averaged over to obtain an ROI mean amplitude value for both the N400 and LPC.

Experiment 2: Lateral Prime

ANOVA Results, N400 (Type: Category)

Predictor	df_{Num}	df_{Den}	Epsilon	F	p	η_g^2
VF	1.00	23.00		2.68	0.115	0.01
strength	1.79	41.15	0.89	31.71	0.000	0.10
strength × VF	1.86	42.82	0.93	2.01	0.149	0.01

Bayes Factor favoring interaction model over main effects model: 0.18 ± 3.57%.

ANOVA Results, N400 (Type: Association)

Predictor	df_{Num}	df_{Den}	Epsilon	F	p	η_g^2
VF	1.00	23.00		7.16	0.013	0.02
strength	1.66	38.07	0.83	25.50	0.000	0.14
strength × VF	2.00	45.89	1.00	2.42	0.100	0.01

Bayes Factor favoring interaction model over main effects model: 0.18 ± 3.07%.

ANOVA Results, LPC (Type: Category)

Predictor	df_{Num}	df_{Den}	Epsilon	F	p	η_g^2
VF	1.00	23.00		3.28	0.083	0.01
strength	1.71	39.35	0.86	44.51	0.000	0.14
strength × VF	1.87	42.95	0.93	1.97	0.154	0.01

Bayes Factor favoring interaction model over main effects model: 0.16 ± 1.97%.

ANOVA Results, LPC (Type: Association)

Predictor	df_{Num}	df_{Den}	Epsilon	F	p	η_g^2
VF	1.00	23.00		19.85	0.000	0.04
strength	1.80	41.29	0.90	45.10	0.000	0.16
strength × VF	1.85	42.66	0.93	2.95	0.067	0.01

Bayes Factor favoring interaction model over main effects model: 0.17 ± 2.24%.

Note. df_{Num} indicates degrees of freedom numerator. df^{Den} indicates degrees of freedom denominator. Epsilon indicates Greenhouse-Geisser multiplier for degrees of freedom, *p*-values and degrees of freedom in the table incorporate this correction. η_g^2 indicates generalized eta-squared. Electrode was averaged over to obtain an ROI mean amplitude value for both the N400 and LPC.

References

Abraham, W. C., & Robins, A. (2005). Memory retention–the synaptic stability versus plasticity dilemma. *Trends in Neurosciences, 28*(2), 73–78.

Anaki, D., Faust, M., & Kravetz, S. (1998). Cerebral hemispheric asymmetries in processing lexical metaphors. *Neuropsychologia, 36*(4), 353–362.

Atchley, R. A., & Kwasny, K. M. (2003). Using event-related potentials to examine hemispheric differences in semantic processing. *Brain and Cognition, 53*(2), 133–138.

Banich, M. T. (2002). The divided visual field technique in laterality and interhemispheric integration. In K. Hugdahl (Ed.), *Experimental methods in neuropsychology* (pp. 47–64). New York, NY: Kluwer.

Bates, D., Maechler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1–48.

Battig, W. F., & Montague, W. E. (1969). Category norms of verbal items in 56 categories A replication and extension of the connecticut category norms. *Journal of Experimental Psychology, 80*(3), 1–46. https://doi.org/10.1037/h0027577

Beeman, M. (1998). Coarse semantic coding and discourse comprehension. *Right hemisphere language comprehension: Perspectives from cognitive neuroscience*, 255-284.

Beeman, M. J., & Chiarello, C. (1998). Complementary right-and left-hemisphere language comprehension. *Current Directions in Psychological Science, 7*(1), 2–8.

Beeman, M., Friedman, R. B., Grafman, J., Perez, E., Diamond, S., & Lindsay, M. B. (1994). Summation priming and coarse semantic coding in the right hemisphere. *Journal of Cognitive Neuroscience, 6*(1), 26–45.

Blake, M. L., Tompkins, C. A., Scharp, V. L., Meigh, K. M., & Wambaugh, J. (2015). Contextual Constraint Treatment for coarse coding deficit in adults with right hemisphere brain damage: Generalisation to narrative discourse comprehension. *Neuropsychological Rehabilitation, 25*(1), 15–52.

Bouaffre, S., & Faita-Ainseba, F. (2007). Hemispheric differences in the time-course of semantic priming processes: Evidence from event-related potentials (ERPs). *Brain and Cognition, 63*(2), 123–135.

Burgess, C., & Chiarello, C. (1996). Neurocognitive mechanisms underlying metaphor comprehension and other figurative language. *Metaphor and Symbol, 11*(1), 67–84.

Burgess, C., & Simpson, G. B. (1988). Neuropsychology of lexical ambiguity resolution: The contribution of divided visual field studies. In *Lexical ambiguity resolution* (pp. 411-430). Morgan Kaufmann.

Burgess, C., & Simpson, G. B. (1988b). Cerebral hemispheric mechanisms in the retrieval of ambiguous word meanings. *Brain and Language, 33*(1), 86–103.

Chiarello, C. (1985). Hemisphere dynamics in lexical access: Automatic and controlled priming. *Brain and Language, 26*(1), 146–172.

Chiarello, C., Burgess, C., Richards, L., & Pollock, A. (1990). Semantic and associative priming in the cerebral hemispheres: Some words do, some words don't… sometimes, some places. *Brain and Language, 38*(1), 75–104.

Chiarello, C., & Richards, L. (1992). Another look at categorical priming in the cerebral hemispheres. *Neuropsychologia, 30*(4), 381–392.

Chiarello, C., Senehi, J., & Nuding, S. (1987). Semantic priming with abstract and concrete words: Differential asymmetry may be postlexical. *Brain and Language, 31*(1), 43–60.

Cools, R. (2019). Chemistry of the Adaptive Mind: Lessons from Dopamine. *Neuron, 104*(1), 113–131.

Coulson, S., & Wu, Y. C. (2005). Right hemisphere activation of joke-related information: An event-related brain potential study. *Journal of Cognitive Neuroscience, 17*(3), 494–506.

Deacon, D., Grose-Fifer, J., Yang, C. M., Stanick, V., Hewitt, S., & Dynowska, A. (2004). Evidence for a new conceptualization of semantic representation in the left and right cerebral hemispheres. *Cortex, 40*(3), 467–478.

De Deyne, S., Kenett, Y. N., Anaki, D., Faust, M., & Navarro, D. (2017). Large-scale network representations of semantics in the mental lexicon. In M. N. Jones (Ed.), Big data in cognitive science (pp. 174-202). Routledge/Taylor & Francis Group.

Diaz, M. T., & Eppes, A. (2018). Factors influencing right hemisphere engagement during metaphor comprehension. *Frontiers in Psychology, 9*, 414.

Eglin, M. (1987). Interference and priming within and across visual fields in a lexical decision task. Neuropsychologia, 25(4), 613-624.

Evans, K. M. and Federmeier, K. D. (2008). Hemispheric asymmetries in verbal memory. In M. Guadagnoli, A. S. Benjamin, J. S. de Belle, B. Etnyre, and T. A. Polk (Eds.), *Advances in Psychology, Volume 139, Human Learning: Biology, Brain, and Neuroscience* (pp. 33-44). Holland: Elsevier.

Faust, M., Ben-Artzi, E., & Vardi, N. (2012). Semantic processing in native and second language: Evidence from hemispheric differences in fine and coarse semantic coding. *Brain and Language, 123*(3), 228–233.

Faust, M., & Kahana, A. (2002). Priming summation in the cerebral hemispheres: Evidence from semantically convergent and semantically divergent primes. *Neuropsychologia, 40*(7), 892–901.

Faust, M., & Lavidor, M. (2003). Semantically convergent and semantically divergent priming in the cerebral hemispheres: Lexical decision and semantic judgment. *Cognitive Brain Research, 17*(3), 585–597.

Federmeier, K. D. (2007). Thinking ahead: The role and roots of prediction in language comprehension. *Psychophysiology, 44*(4), 491–505.

Federmeier, K. D., & Kutas, M. (1999). Right words and left words: Electrophysiological evidence for hemispheric differences in meaning processing. *Cognitive Brain Research, 8*(3), 373–392.

Federmeier, K. D., Wlotko, E. W., & Meyer, A. M. (2008). What's 'Right'in Language Comprehension: Event-Related Potentials Reveal Right Hemisphere Language Capabilities. *Language and Linguistics Compass, 2*(1), 1–17.

Francis, W. N., & Kucera, H. (1967). *Computational analysis of present-day American English.* Providence, RI: Brown University Press.

Grose-Fifer, J., & Deacon, D. (2004). Priming by natural category membership in the left and right cerebral hemispheres. *Neuropsychologia, 42*(14), 1948–1960.

Hampton, J. A., & Gardiner, M. M. (1983). Measures of internal category structure: A correlational analysis of normative data. *British Journal of Psychology, 74*(4), 491–516.

Huang, H. W., Lee, C. L., & Federmeier, K. D. (2010). Imagine that! ERPs provide evidence for distinct hemispheric contributions to the processing of concrete and abstract concepts. *NeuroImage, 49*(1), 1116–1123.

Hunt, K. P., & Hodge, M. H. (1971). Category-item frequency and category-name meaningfulness (m'): Taxonomic norms for 84 categories. *Psychonomic Monograph Supplements.*

Jordan, T. R., & Patching, G. R. (2003). Assessing effects of stimulus orientation on perception of lateralized words and nonwords. *Neuropsychologia, 41*(12), 1693–1702.

Jordan, T. R., & Patching, G. R. (2006). Assessing effects of fixation demands on perception of lateralized words: A visual window technique for studying hemispheric asymmetry. *Neuropsychologia, 44*(5), 686–692.

Jordan, T. R., Patching, G. R., & Milner, A. D. (1998). Central fixations are inadequately controlled by instructions alone: Implications for studying cerebral asymmetry. *The Quarterly Journal of Experimental Psychology Section A, 51*(2), 371–391.

Jordan, T. R., Patching, G. R., & Milner, A. D. (2000). Lateralized word recognition: Assessing the role of hemispheric specialization, modes of lexical access, and perceptual asymmetry. *Journal of Experimental Psychology: Human Perception and Performance, 26*(3), 1192.

Jordan, T. R., Redwood, M., & Patching, G. R. (2003). Effects of form familiarity on perception of words, pseudowords, and nonwords in the two cerebral hemispheres. *Journal of Cognitive Neuroscience, 15*(4), 537–548.

Jung-Beeman, M. (2005). Bilateral brain processes for comprehending natural language. *Trends in Cognitive Sciences, 9*(11), 512–518.

Kandhadai, P., & Federmeier, K. D. (2007). Multiple priming of lexically ambiguous and unambiguous targets in the cerebral hemispheres: The coarse coding hypothesis revisited. *Brain Research, 1153*, 144–157.

Kandhadai, P., & Federmeier, K. D. (2008). Summing it up: Semantic activation processes in the two hemispheres as revealed by event-related potentials. *Brain Research, 1233*, 146–159.

Kandhadai, P., & Federmeier, K. D. (2010a). Hemispheric differences in the recruitment of semantic processing mechanisms. *Neuropsychologia, 48*(13), 3772–3781.

Kandhadai, P., & Federmeier, K. D. (2010b). Automatic and controlled aspects of lexical associative processing in the two cerebral hemispheres. *Psychophysiology, 47*(4), 774–785.

Krashen, S. D. (1976). *Cerebral asymmetry. In Studies in neurolinguistics* (pp. 157–191). Academic Press.

Kutas, M., & Federmeier, K. D. (2011). Thirty years and counting: Finding meaning in the N400 component of the event-related brain potential (ERP). *Annual Review of Psychology, 62*, 621–647.

Lambon Ralph, M. A., Jefferies, E., Patterson, K., & Rogers, T. T. (2017). The neural and computational bases of semantic cognition. *Nature Reviews Neuroscience, 18*(1), 42–55.

Livesay, K., & Burgess, C. (2003). Mediated priming in the cerebral hemispheres. *Brain and Cognition, 53*(2), 283–286.

Marcel, A. J., & Patterson, K. E. (1978). Word recognition and production: Reciprocity in clinical and normal studies. *Attention and Performance VII*, 209–226.

McCloskey, M. E., & Glucksberg, S. (1978). Natural categories: Well defined or fuzzy sets? *Memory & Cognition, 6*(4), 462–472.

McEvoy, C. L., & Nelson, D. L. (1982). Category name and instance norms for 106 categories of various sizes. *The American Journal of Psychology*, 581–634.

Metusalem, R., Kutas, M., Urbach, T. P., & Elman, J. L. (2016). Hemispheric asymmetry in event knowledge activation during incremental language comprehension: A visual half- field ERP study. *Neuropsychologia, 84*, 252–271.

Metusalem, R., Kutas, M., Urbach, T. P., Hare, M., McRae, K., & Elman, J. L. (2012). Generalized event knowledge activation during online sentence comprehension. *Journal of Memory and Language, 66*(4), 545–567.

Michimata, C. (1987). *Lateralized effects of semantic priming in lexical decision tasks: Examinations of the time course of semantic activation build-up in the left and right cerebral hemispheres.* Univ. of Southern California. Ph.D. dissertation.

Mitchell, R. L., Vidaki, K., & Lavidor, M. (2016). The role of left and right dorsolateral prefrontal cortex in semantic processing: A transcranial direct current stimulation study. *Neuropsychologia, 91*, 480–489.

Musslick, S., Jang, S. J., Shvartsman, M., Shenhav, A., & Cohen, J. D. (2018). Constraints associated with cognitive control and the stability-flexibility dilemma. In *CogSci*.

Nelson, D. L., McEvoy, C. L., & Schreiber, T. A. (2004). The University of South Florida free association, rhyme, and word fragment norms. *Behavior Research Methods, Instruments, & Computers, 36*(3), 402–407.

Oldfield, R. C. (1971). The assessment and analysis of handedness: The Edinburgh inventory. *Neuropsychologia, 9*(1), 97–113.

Olichney, J. M., Van Petten, C., Paller, K. A., Salmon, D. P., Iragui, V. J., & Kutas, M. (2000). Word repetition in amnesia: Electrophysiological measures of impaired and spared memory. *Brain, 123*(9), 1948–1963.

Patching, G. R., & Jordan, T. R. (1998). Increasing the benefits of eye-tracking devices in divided visual field studies of cerebral asymmetry. *Behavior Research Methods, Instruments, & Computers, 30*(4), 643–650.

Richards, L., & Chiarello, C. (1995). Depth of associated activation in the cerebral hemispheres: Mediated versus direct priming. *Neuropsychologia, 33*(2), 171–179.

Schapiro, A. C., McClelland, J. L., Welbourne, S. R., Rogers, T. T., & Lambon Ralph, M. A. (2013). Why bilateral damage is worse than unilateral damage to the brain. *Journal of Cognitive Neuroscience, 25*(12), 2107–2123.

Shapiro, S. I., & Palermo, D. S. (1970). Conceptual organization and class membership: Normative data for representatives of 100 categories. *Psychonomic Monograph Supplements.*

Simpson, G. B. (1994). Context and the processing of ambiguous words. *Handbook of Psycholinguistics, 22*, 359–374.

Snijders, T. A. B., & Bosker, R. J. (2012). Multilevel analysis: An introduction to basic and advanced multilevel modeling. Thousand Oaks: Sage Publishing.

Stram, D. O., & Lee, J. W. (1994). Variance components testing in the longitudinal mixed effects model. *Biometrics, 50*, 1171–1177. https://doi.org/10.2307/2533455

Stram, D. O., & Lee, J. W. (1995). Correction to: Variance components testing in the longitudinal mixed effects model. *Biometrics, 51*, 1196. https://doi.org/10.2307/2533038

Swaab, T. Y., Brown, C., & Hagoort, P. (1998). Understanding ambiguous words in sentence contexts: Electrophysiological evidence for delayed contextual selection in Broca's aphasia. *Neuropsychologia, 36*(8), 737–761.

Team, R. C. (2020). R: A Language and Environment for Statistical Computing, version 4.0. 2. Vienna, Austria: R Foundation for Statistical Computing. *Verfügbar unter* https://www.R-project.org.

Titone, D. (1998). Hemispheric differences in context sensitivity during lexical ambiguity resolution. *Brain and Language, 65*(3), 361–394.

Van Overschelde, J. P., Rawson, K. A., & Dunlosky, J. (2004). Category norms: An updated and expanded version of the norms. *Journal of Memory and Language, 50*(3), 289–335.

Van Petten, C., & Kutas, M. (1991). Influences of semantic and syntactic context on open- and closed-class words. *Memory & Cognition, 19*(1), 95–112.

Walker, E., & Ceci, S. J. (1985). Semantic priming effects for stimuli presented to the right and left visual fields. *Brain and Language, 25*(1), 144–159.

Willits, J. A., Amato, M. S., & MacDonald, M. C. (2015). Language knowledge and event knowledge in language use. *Cognitive Psychology, 78*, 1–27.

Wlotko, E. W., & Federmeier, K. D. (2013). Two sides of meaning: The scalp-recorded N400 reflects distinct contributions from the cerebral hemispheres. *Frontiers in Psychology, 4*, 181.

Zaidel, E., White, H., Sakurai, E., & Banks, W. (1988). Hemispheric locus of lexical congruity effects: Neuropsychological reinterpretation of psycholinguistic results. In *Right hemisphere contributions to lexical semantics* (pp. 71–88). Berlin, Heidelberg: Springer.