The N400's 3 As: Association, Automaticity, Attenuation (and Some Semantics Too)

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12   Abstract

13   The N400 waveform carries new insight into the nature of linguistic processing and may shed

14   light into the automaticity of priming word relationships. We investigated semantic and

15   associative word pairs in classic lexical decision and letter search tasks to examine their

16   differences in cognitive processing. Normed database information was used to create

17   orthogonal semantic and associative word relationships to clearly define N400 waveforms and

18   priming for these pairs. Participants showed N400 reduction for related word pairs, both

19   semantic and associative, in comparison to unrelated word pairs. This finding was consistent

20   across both lexical decision and letter search tasks, indicating automatic access for both

21   types of relatedness. Nonword pairs showed N400 waveforms that resembled unrelated word

22   pairs, indicating the controlled examination of non-advantageous words. Response latency

23   data nearly mirrored the EEG finding. Priming was found for semantic and associative word

24   relationships, while Nonword pairs were generally slower than unrelated word pairs.

25   *Keywords:* association, semantics, priming, N400, EEG, lexical decision, letter search

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27   Semantic facilitation through priming occurs when a related cue word speeds the

28 processing of a following target word (Meyer & Schvaneveldt, 1971). For example, if a person

29 is reading about a yacht race, the word boat is easier to process because of previous

30 activation in semantic memory. Research suggests that priming transpires by both automatic

31 and controlled processes. The automatic model proposes that related words are linked in the

32 brain due to overlapping features (Collins & Loftus, 1975). Target words are activated

33 without conscious control due to automatic spreading activation within related cognitive

34 networks. Lexical and feature networks are thought to be stored separately, so that semantic

35 priming is the activation from the feature network feeding back into the lexical level (Stolz &

36 Besner, 1996). The overlap of a second word's semantic relatedness makes word recognition

37 easier because it, in essence, has already been processed. The controlled process model

38 proposes that people actively use cognitive strategies to connect related words together.

39 Neely (1991) describes both expectancy generation and post lexical matching as ways that

40 target word processing may be speeded. In expectancy generation, people consciously

41 attempt to predict the words and ideas that will appear next, especially in sentences.

42 Whereas in post lexical matching, people delay processing of the second target word so that

43 it can be compared to the cue word for evaluation. In both cases, the target word is

44 quickened by its relationship to the cue word.

45   Traditionally, priming has been tested with a simple word or nonword decision called a

46 lexical decision task. Participants are shown a cue or priming word, followed by a related or

47 unrelated target word for the word/nonword judgment. Priming occurs when the judgment

48 for the target is speeded for related pairs over unrelated pairs. Lexical decision tasks have

49 been criticized for their inability to distinguish between automatic and controlled processing,

50 so both single presentation lexical decision tasks and masked priming manipulations have

51 been introduced to negate controlled processing (Ford, 1983). In a single lexical decision

52 task, participants assess both the cue and target word so that they are not as overtly paired

53 together. Experimenters might also mask or distort the cue word, so that participants do not

54 believe they can perceive the cue word. Even though words are garbled, word perception

55 occurs at a subliminal level and often facilitates the target word with automatic activation.

Priming in the Brain

57   Event related potentials (ERPs) are used to distinguish both the nature of priming and

58 the automaticity of priming. The use of ERPs is advantageous, measuring brain activity per

59 an electroencephalogram (EEG) with good temporal resolution, and is thought to be a

60 sensitive measure of real-time language processing (Kutas & Federmeier, 2000). The N400 is

61 a negative waveform that occurs 400 msec after the participant is presented with a stimulus

62 (Brown & Hagoort, 1993). The N400 has been described as a "contextual integration

63 process", in which meanings of words are integrated and functions, bridging together sensory

64 information and meaningful representations (Kutas & Federmeier, 2000). The amplitude of

65 the N400 is sensitive to contextual word presentations, varying systematically with semantic

66 processing. This change justifies the use of the N400 as an appropriate dependent measure

67 for lexical decision tasks. When presented with related words, there is an attenuation of the

68 N400, meaning a more positive waveform when compared to unrelated word presentation.

69 This difference in waveforms indicates a lessened contextual integration process because word

70 meanings are already activated.

71   Multiple theories of the N400, however, have been proposed and debated on what

72 explicitly the N400 indexes. On one hand, processes associated with the N400 are believed to

73 occur post-word recognition. Brown and Hagoort (1993) examined a lexical decision task

74 paired with masked priming. No differences were found in the N400 wave between related

75 and unrelated words in the masked prime condition. Brown and Hagoort (1993) concluded

76 that this finding indicated that semantic activation was a controlled process, because

77 attenuation only occurred when words were known. Thus, an "integrating" process

78 transpires with semantic information from of multi-word characteristic representations

79 (Hagoort, Baggio, & Willems, 2009; Kutas & Federmeier, 2011). This condition supposedly

80 rules out automatic processes, because the masked prime condition only allowed automatic

81 processes to take place. Masked priming did not allow the participants to consciously name

82 the prime words they had seen; thus, they were not able to purposefully employ conscious

83 cognitive strategies in processing these words. However, Deacon, Hewitt, Yang, and Nagata

84 (2000) have found that with shorter stimulus onset asynchronies (SOAs), this effect of

85 masked priming disappears. SOAs are the time interval between the prime word presentation

86 and the target word appearance. Short SOAs are thought to only allow for automatic

87 processing because the controlled, attention based processing has not had time yet to occur.

88 Their study showed the masked primes long enough to enhance priming, while remaining

89 imperceptible. With these modifications, Deacon, Dynowska, Ritter, and Grose-Fifer (2004)

90 found equal N400 attenuation for the masked and unmasked primes. This result would

91 indicate that automatic activation was taking place, as the masked prime condition did not

92 allow controlled processes to take place. Kiefer (2002) has found similar results in the N400

93 using different masking levels, which kept judgment ability of prime words below chance.

94   A separate theory suggests that N400 effects are seen pre-word recognition. The N400

95 was found to be sensitive to pseudo- or Nonwords, even when absent a resemblance to real

96 word counterparts. Deacon et al. (2004) explain that this result could imply processes that

97 precede word recognition, such as orthographic or phonological analysis. More recently,

98 Federmeier and Laszlo (2009) suggested that the N400 indexes access to semantic memory.

99 Meaningful stimuli representing a multitude of modalities indicates a sensitivity with

100 attention, albeit still can occur in its absence. Processing from modalities can integrate,

101 yielding different meanings from different contexts, respectively (Federmeier & Laszlo, 2009).

102 Regardless of competing aspects as to what the N400 is estimated to index, vital insights

103 have been made crossing different cognitive domains, with the N400 illuminating aspects

104 originating from these different domains (Kutas & Federmeier, 2011).

105   Rolke, Heil, Streb, and Hennighausen (2001) used the attention blink rapid serial

visual presentation (RSVP) paradigm, in which participants identified target words within a stream of distractor words presented in a different color. By selecting items via specifying the row and column within a matrix, participants identified the target word they had previously seen. These studies compare to masked priming, and show automatic activation of semantic information even when targets were missed (Rolke et al., 2001). Letter search tasks also reduce semantic priming by focusing attention on the lexical level instead of a feature meaning level (Friedrich, Henik, & Tzelgov, 1991). In this task, participants are asked to determine if cue and target words contain a specific letter presented. Stolz and Besner (1996) stipulate that this eliminated or reduced priming indicates non-automatic semantic priming. However, it is also important to note that Tse and Neely (2007) did yield evidence that letter search primes produced semantic priming for low-frequency targets, albeit not for high-frequency targets. In Smith and Besner (2001) letter search and lexical decision combined study, they found that the letter search task eliminated semantic priming when compared to unrelated word pairs and the lexical decision task. Yet, Marí-Beffa, Valdés, Cullen, Catena, and Houghton (2005) found ERP evidence for semantic processing of the prime word during letter search tasks with the attenuation of the N400.

Association

From a theoretical standpoint, the relation between associative and semantic processing follows a deep line of research. Associative word pairs are words that are linked in one's memory by contextual relationships, such as basket and picnic (Nelson, McEvoy, & Schreiber, 2004). Another example would be a word pair like alien and predator, which would be associatively linked for Americans due to the movies and popular culture. Semantic word pairs are those linked by their shared features and meaning, such as *wasp* and *bee* (Buchanan, Holmes, Teasley, & Hutchison, 2013; McRae, Cree, Seidenberg, & McNorgan, 2005; Vinson & Vigliocco, 2008).

Associative and semantic relationships between words are experimentally definable by

the use of normed databases. Maki, McKinley, and Thompson (2004) took the online

dictionary, WordNet (Felbaum, 1998), and used software by Patwardhan, Banerjee, and

Pedersen (2003) to create a database of words displaying the semantic distance between

individual words. This database displays the relatedness between two words by measuring

how semantically close words appear in hierarchy, or the JCN (Jiang & Conrath, 1997). JCN

measures the word pairs' informational distance from one another, or their semantic

similarities. Therefore, a low JCN score demonstrates a close semantic relationship.

Additionally, we can use a measure of semantic feature overlap to examine the semantic

relatedness between word pairs (Buchanan et al., 2013; McRae et al., 2005; Vinson &

Vigliocco, 2008), and this measure is factorally related to JCN as a semantic measure (Maki

& Buchanan, 2008). Another useful database, created by Nelson et al. (2004), is centered on

the associative relationships between words. Participants were given cue words and asked to

write the first word that came to mind. These responses were asked of and averaged over

many participants. The probability of a cue word eliciting the target word is called the

forward strength (FSG). For example, when participants are shown the word *lost*, the most

common response is *found*, which has a FSG of .75 or occurs about 75% of the time.

Separating Semantic and Associative Priming

A meta-analytic review from Lucas (2000) examined semantic priming in the absence

of association. Effect sizes for semantic priming alone were lower than associative priming.

However, with the addition of an associative relationship to an existing semantic relationship,

priming effects nearly doubled, also known as the associative boost (Moss, Ostrin, Tyler, &

Marslen-Wilson, 1995). This result suggests that semantic relationships, that concurrently

have associations, can increase priming effects. Priming effects, therefore, are suggested not

to be based on association in isolation. Hutchison (2003) argues against Lucas, suggesting

positive evidence for associative priming. Automatic priming was sensitive to associative

strength as well as feature overlap. These points of contention provide impetus for more

158 research centering on distinctions between associative and semantic priming.

159   With the databases described above, orthogonal word pair stimuli can be created to
160 examine associative and semantic priming individually and indeed, priming can be found for
161 each relation separately (Buchanan, 2010). Few studies have directly compared associative
162 and semantic relationships, especially focusing on the brain. Deacon et al. (2004) claim that
163 hemispheric differences exist in lexico-semantic representation, comparing associative and
164 semantic priming. Deacon et al. concluded that semantic features are localized in the right
165 hemisphere, whereas association is localized more within the left hemisphere of the brain.
166 The current study, with an aim to elaborate on basic theoretical questions such as the
167 relationship between associative and semantic processing, examined the relationship between
168 N400 activation, priming task, and word relationship type. Participants were given both a
169 single lexical decision and letter search task, along with separate semantic, associative, and
170 unrelated word pairs. We expected that the N400 modulation might vary from the different
171 types of word relation, which would indicate differences in cognitive processing and word
172 organization.

Method

Participants

175   Twenty undergraduate students were recruited from the University of Mississippi
176 (thirteen women and seven men), and all volunteered to participate. All participants were
177 English speakers. The experiment was carried out with the permission of the University's
178 Institutional Review Board, and all participants signed corresponding consent forms. One
179 participant's EEG data was corrupted and could not be used, and another participant was
180 excluded for poor task performance (below chance), leaving eighteen participants (twelve
181 women and six men).

Apparatus

The system used was a 32 Channel EEG Cap connected to a NuAmps monopolar digital amplifier, which was connected to a computer running SCAN 4.5 software to record the data. The SCAN software was capable of managing continuous digital data captured by the NuAmps amplifier. STIM2 was used to coordinate the timing issues associated with Windows operating system and collecting EEG data on a separate computer. STIM2 also served as the software base for programming and operating experiments of this nature. The sensors in the EEG cap were sponges injected with 130 ml of electrically conductive solution (non-toxic and non-irritating). Also, to protect the participants and equipment, a surge protector was used at all times during data acquisition. The sensors recorded electrical activity just below the scalp, displaying brain activation. This data was amplified by the NuAmps hardware, and processed and recorded by the SCAN software.

Materials

This experiment consisted of 360 word pairs separated into levels in which the target words were unrelated to the prime (120), semantically associated to the prime (60), associatively related to the prime (60), or were nonwords (120). We used only a small number of related word pairs to try to reduce expectancy effects described in the introduction (Neely, 1991). These 360 pairs were split evenly between the lexical decision and letter search task, therefore, each task contained 60 unrelated pairs, 30 semantically related pairs, 30 associatively related pairs, and 60 nonword pairings. The ratio of yes/no correct answers for words and nonwords in the lexical decision task was 2:1 and 1:1 yes/no decisions in the letter search task. Splitting the nonword pairs over both the letter search and lexical decision task created a higher yes/no ratio for the lexical decision task, which was controlled for by mixing both tasks together.

The stimuli were selected from the Nelson et al. (2004) associative word norms and Maki et al. (2004) semantic word norms. The associative word pairs were chosen using the

208 criteria that they were highly associatively related, having an FSG score greater than .50;

209 with little or no semantic similarities, determined by having a JCN score of greater than 20.

210 An example of an associative pair would be *dairy-cow*. The semantic word pairs were chosen

211 using the criteria that they had a high semantic relatedness shown in a JCN of 3 or less; and

212 were not associatively related, having an FSG of less than .01 (e.g., *inn-lodge*). For

213 associative word pairs, the mean FSG was $M = .57$ ($SD = .11$) for the LDT, and $M = .59$

214 ($SD = .10$) for the LST. The JCN was high for associative pairs, LDT $M = 20.20$ ($SD =$

215 1.58) and LST $M = 21.12$ ($SD = 1.77$). For semantic pairs, the JCN was low for both the

216 LDT, $M = 0.18$ ($SD = 0.28$), and LST, $M = 0.25$ ($SD = 0.33$). The FSG was kept low for

217 the semantic pairs, LDT, $M = .02$ ($SD = .01$), and LST, $M = .02$ ($SD = .01$).

218   The unrelated words were chosen so that they had no similarities (were unpaired in the

219 databases), such as *blender* and *compass.* For Nonword pairs, the target word had one letter

220 changed so that it no longer represented a real word, yet the structure was left intact to

221 require that the participant process the word cognitively. Essentially, Nonwords were

222 orthographically similar to its real word counterpart, except for the change in a single letter.

223 For example, the word *pond* can be changed to *pund* to produce a Nonword target. All

224 materials and their database values can be found at our Open Science Foundation page:

225 https://osf.io/h5sd6/.

Procedure

227   Testing occurred in one session consisting of six blocks of acquired data, broken up by

228 brief rest periods. Before each participant was measured, the system was configured to the

229 correct settings, and the hardware prepared. Two reference channels, which define zero

230 voltage, were placed on the right and left mastoid bones.

231   We modeled the current task after Smith and Besner (2001) lexical decision and letter

232 search task combination. Smith and Besner (2001) used a choice task procedure, where the

233 color of the target word indicated the target task. One color denoted lexical decision with

²³⁴ another color denoting letter search. The lexical decision task involved participants observing

²³⁵ a word onscreen and deciding whether or not it was a word or Nonword (such as *tortoise* and

²³⁶ *werm*). Nonrelated word pairs were created by taking prime and target words from related

²³⁷ pairs and randomly rearranging them to eliminate relationships between primes and targets.

²³⁸ The letter search task involved participants observing a word onscreen and deciding whether

²³⁹ it contained a repeated letter or not (i.e., the repeated letters in *doctor* versus no repeated

²⁴⁰ letters in *nurse*). Words were presented onscreen, and would stay there until the participant

²⁴¹ pressed the corresponding keys for yes and no. Participant responses were time limited and

²⁴² truncated to 60 seconds. The 1 and 9 keys were used on the number row of the keyboard, in

²⁴³ the participant's lap to help eliminate muscle movement artifact in the data.

²⁴⁴ 　　　Participants were first given instructions on how to perform the lexical decision task,

²⁴⁵ followed by 15 practice trials. Next, they were given instructions on how to judge the letter

²⁴⁶ search task, followed by 15 practice trials. Participants were then given a practice session

²⁴⁷ with both letter search and lexical decision trials mixed together. Trials were color coded for

²⁴⁸ the type of decision participants had to complete (i.e., letter search was red, while lexical

²⁴⁹ decision was green). The experiment made use of six sets of 60 randomly assigned word pairs

²⁵⁰ for a total of 360 trials. These trials were presented in Arial 19-point font, and the inter-trial

²⁵¹ interval was set to two seconds to allow complete recording of the N400 waveform. Trials

²⁵² were recorded in five minute blocks, and between blocks participants were allowed to rest to

²⁵³ prevent fatigue. The current task differed from Smith and Besner (2001) in that participants

²⁵⁴ responded to every word (prime and targets), instead of only targets. Therefore, there was no

²⁵⁵ typical fixed stimulus onset asynchrony (SOA) because participant responses were self-paced.

Results

N400 Waveform Analysis

²⁵⁸ 　　　The data were cleared of artifact data using EEGLAB, an open source MATLAB tool

²⁵⁹ for processing electrophysiological data. The program automatically scanned for and

removed artifacts caused by eye-blinking. Next, the datasets were visually inspected and any remaining corrupted sections were removed manually. Ninety percent of the data was retained across all trials and stimulus types after muscular artifact data were removed. However, a loss rate of 20-30 percent is not uncommon, especially with older EEG systems. The data were combined by task and stimulus type exclusively for the second word in each pair. Five sites were chosen to examine priming for nonwords, associative and semantic word pairs based on a survey of the literature. Fz, FCz, Cz, CPz, and Pz were used from the midline. Oz was excluded due to equipment problems across all participants. Using MATLAB, the N400 area under the curve was calculated for each electrode site, stimulus, and task (averaging over trials) 300-500 msec after stimuli presentation. A constant score was subtracted from all EEG points to ensure all curves were below zero for area under the curve calculations.

Van Selst and Jolicoeur (1994) describe that outlier elimination procedures can be affected by factors such as sample size or data skewness. They, as well as Miller (1991), describe procedures for adaptive outlier criteria based on sample size to correct for this any bias due to sample size. We utilized a non-recursive procedure with a moving criterion for outlier elimination. For example, traditional outlier identification may be based on a z-score criteria of two or more standard deviations away from the mean score. In the Van Selst and Jolicoeur (1994), this cut-off z-score is adjusted by sample size, and therefore, we used the average of their recommendations for 15 to 20 participants, $z_{critical} = 2.36$. The non-recursive procedure involves only examing the data once for outliers, rather than continuing to screen for outliers iteratively until no outliers remained. Across 18 participants by five sites, three outlying data points were identified and subsequently removed from further analysis. Data were also screened for parametric assumptions of linearity, normality, homogeneity, and homoscedasticity. The data were slightly negatively skewed, but with the large quantity of data for each participant as well as the choice of analysis, test statistics should be robust to this slight skew.

To analyze this data, we used multilevel models (MLM) to control for correlated error due to repeated measures of sites and stimulus type for each participant (Gelman, 2006). These models were calculated using the *nlme* package in *R* (Pinheiro, Bates, Debroy, Sarkar, & Team, 2017). First, a model with only the intercept was compared to a model with participants as a random intercept factor. Random intercepts allow each participant to have different average scores for areas under the curve or peak latency (see below). If the random intercept model was better than the intercept only model, then all forthcoming models would include participants as a random intercept factor. Models were compared only to the previous step and were deamed "significant" if the likelihood ratio difference score, $\Delta\chi^2$ was greater than to be expected given the change in degrees of freedom between models. Therefore, the *p*-values for each $\Delta\chi^2$ were calculated based on Δdf, and α was set to .05. The two tasks, lexical desicion and letter search, were analyzed in separate models with the area under the curve as the dependent variable. The independent variables included the dummy coded site location as a control variable, followed by stimulus type coded as a dummy variable. In this analysis, we wished to compare each stimulus type to every other stimulus type, and therefore, we set α for these six comparisons to $.05/6 = .008$. The stimuli variable was recoded to examine all pairwise comparisons.

Table 1 includes the model statistics for the lexical decision and letter search tasks. Participants were included as a random intercept factor, as this model was significantly better than an intercept only model, $p < .001$. The addition of the predictors of site and type of stimulus were also significant for both models, $p < .001$ and $p = .003$. Table 2 includes the estimates for each pairwise comparison for word stimulus type. For the lexical decision task, we found that nonwords and unrelated had significantly larger areas under the curve than related word pairs. Nonwords and unrelated pairs were not different using our corrected α value. This find replicated previous work that the N400 was larger for unexpected words, while related word pairs showed attenuation. Semantic and associative stimuli did not show differences in their area under the curve. Figure 1 displays the ERP waveforms, separated by

site, for the lexical decision task. For the letter search task, a similar pattern emerges for

nonwords, in that they showed larger areas under the curve than all other stimuli. However,

we did not find attenuation for related words, as unrelated, semantic, and associative words

showed the same area under the curve in this task. Figure 2 portrays the letter search task.

The two gray lines represent unrelated and nonwords, which have larger areas under the

curve than the two black lines, which represent semantic and associative word pairs.

Task Performance

One persons data was corrupt for the complete task component, and one participant's

task excluded several of their responses. The missing responses were excluded for this

analysis ($n = 16$ complete with 360 responses, $n = 1$ with 329 responses). Task data were

scored for correctness in the two tasks, and overall performance was around 94% for each

task: LDT, $M = 94.38$ ($SD = 23.03$) and LST, $M = 94.38$ ($SD = 23.03$). Incorrect trials (n

$= 335$) were discarded for the response latency analysis. An analysis of outliers indicated

there were 214 trials with long response latencies, and they were excluded from the analysis.

Two MLM analyses were conducted on each task separately, with stimuli as the

independent variable and response latency as the dependent variable, controlling for

participants as a random factor (see Table 3). In both the lexical decision and letter search

tasks, there were significant improvements in the model by including stimuli as a predictor

over the random intercept model, ps $< .001$. Each stimuli type was compared pairwise, and

α was again set at .008 to control the Type I error rate. Table 4 includes these comparisons

from the dummy coded models, and means with 95% confidence intervals are displayed in

Figure 3. For the lexical decision task, nonwords were slower than all other stimuli types.

Unrelated words were not different from semantic word pairs, but were slower than

associative word pairs. This finding indicated that the lexical decision task showed

associative priming, but not semantic priming; however, there were not response latency

differences for these two related word pair types. In contrast to this finding, and results from

340   the N400 area under the curves, we found priming for both semantic and associative word

341   pairs in the letter search task. Nonwords were again slower than all other stimuli types,

342   followed by unrelated word pairs. Again, semantic and associative pairs were not different.

343   These analyses were examined with the outliers included in the analysis, as we considered

344   that eliminating 214 trials may have skewed the results. The pattern of results did not

345   change, but the differences between unrelated pairs and other stimuli types do become larger.

346   **Discussion**

347   These experiments were designed to explore the differences between N400 activation in

348   the brain following presentation of semantic-only, associative-only, and unrelated word pairs

349   in priming tasks. The N400 data and reaction time data present picture of associative and

350   semantic priming during both lexical decision and letter search task. Because both tasks

351   were designed to reduce controlled processing of cue-target relationships, these findings imply

352   automatic activation of word meanings and associations, even when task demands do not

353   warrant word activation. Nonword activation is more problematic to interpret, as N400

354   waveforms are not different from unrelated word pairs, but reaction time data is much slower.

355   These results, taken together, may illustrate a controlled process search of the lexicon

356   requiring the same activation levels. When an unrelated target word is found in the lexicon,

357   controlled search is terminated, while searching for a nonword continues for more time before

358   the search is terminated. However, Deacon et al. (2000) point to potential issues with the

359   relationship between the N400 and automaticity. Semantic processing, Deacon et al. (2000)

360   discuss, is possible in the absence of attention or a dearth of awareness.

361   Since findings were roughly similar for associative and semantic word pairs, we can

362   postulate that the activation processes for these types of word relatedness are also roughly

363   similar. This experiment cannot separate if the cognitive architecture is different for

364   associations and semantics, but that the automatic mechanisms for priming are comparable.

365   One limitation is that the long stimulus onset times may have allowed for controlled

processing in the reaction time data, but the consistent N400 attenuation suggests a quick search of the lexicon similar to an automatic activation process. Finally, differences in activation across gender need to be explored. Although not conclusive due to sample size, we found that male activation across stimuli was implicated in traditional left Broca?s area, while female activation averaged to central parietal areas. Regardless of any potential differences, the broad sensitivity of the N400 means it can be implemented when investigating how information is stored in the brain. The temporal lobe has been shown to be implicated as a source from the N400, albeit occurs in a flexible manner, varying with different classes of stimuli (Federmeier & Laszlo, 2009). There are sometimes dissociations between the N400 and reaction time measures. The use of the N400 can therefore be seen as an especially relevant dependent measure for the reason that components can only partially be a reflection of semantic processes relating to response latencies (Kutas & Federmeier, 2011).

To date, research has focused on semantic priming and its automaticity without many controls for associative relationships embedded in word pairs. Certainly there is overlap between meaning and context use of words, but these differences can be studied separately using available databases (Hutchison, 2003). Our current study has supported findings by Marí-Beffa et al. (2005), who showed activation during letter search tasks, along with the many studies on automatic activation during masked priming (Deacon et al., 2000; Kiefer, 2002).

Limitations do exist within these experiments. As previously mentioned a larger sample size would increase the power coefficient of the findings. Future studies should focus on the extent of priming in semantic word pairs during a letter search task, which is a controversial topic within the literature. Since our study limited relatedness to associations or semantics, upcoming experiments could examine the interaction between word relationship type of N400 attenuation. Kreher, Holcomb, and Kuperberg (2006) have shown that N400 waveform differences can be attributed to different strengths of semantic relatedness in a linear fashion. With more exploration into the exact priming nature of

393 associations and semantics, we may begin to discover their cognitive mechanisms.

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Table 1

Area under curve model statistics

Model	*df*	AIC	BIC	χ^2	$\Delta\chi^2$	*p*
LDT Intercept	2	5854.50	5862.27	-2925.25	NA	NA
LDT Random Intercept	3	5639.91	5651.57	-2816.96	216.59	< .001
LDT Full	10	5585.86	5624.72	-2782.93	68.05	< .001
LST Intercept	2	5704.00	5711.75	-2850.00	NA	NA
LST Random Intercept	3	5443.21	5454.85	-2718.61	262.78	< .001
LST Full	10	5435.82	5474.60	-2707.91	21.39	.003

Note. AIC: Aikaike Information Criterion, BIC: Bayesian Information Criterion

Table 2

Area under curve model estimates

Task	Predictor	b	SE	t	p
LDT	CZ	-59.86	85.35	-0.70	.484
LDT	FCZ	-124.76	85.35	-1.46	.145
LDT	FZ	-173.07	85.35	-2.03	.043
LDT	PZ	54.22	85.35	0.64	.526
LDT	Unrelated - Nonword	-189.97	76.34	-2.49	.013
LDT	Unrelated - Semantic	331.30	76.34	4.34	< .001
LDT	Unrelated - Associative	301.18	76.34	3.95	< .001
LDT	Nonword - Semantic	521.27	76.34	6.83	< .001
LDT	Nonword - Associative	491.15	76.34	6.43	< .001
LDT	Semantic - Associative	-30.12	76.34	-0.39	.693
LST	CZ	-38.69	73.85	-0.52	.601
LST	FCZ	-61.36	73.58	-0.83	.405
LST	FZ	-50.44	73.58	-0.69	.493
LST	PZ	12.85	74.14	0.17	.862
LST	Unrelated - Nonword	-184.82	65.81	-2.81	.005
LST	Unrelated - Semantic	91.03	66.01	1.38	.169
LST	Unrelated - Associative	43.60	66.21	0.66	.511
LST	Nonword - Semantic	275.86	66.01	4.18	< .001
LST	Nonword - Associative	228.43	66.21	3.45	.001
LST	Semantic - Associative	-47.43	66.41	-0.71	.476

Note. The site control level was considered CPZ. Degrees of
freedom are 335 for lexical decision tasks and 332 for letter search
tasks.

Table 3

Response latency model statistics

Model	df	AIC	BIC	χ^2	$\Delta\chi^2$	p
LDT Intercept	2	43019.73	43031.59	-21507.87	NA	NA
LDT Random Intercept	3	42613.48	42631.25	-21303.74	408.26	< .001
LDT Full	6	42443.72	42479.27	-21215.86	175.76	< .001
LST Intercept	2	45000.97	45012.82	-22498.48	NA	NA
LST Random Intercept	3	44365.19	44382.97	-22179.60	637.78	< .001
LST Full	6	44286.21	44321.77	-22137.10	84.98	< .001

Note. AIC: Aikaike Information Criterion, BIC: Bayesian Information Criterion

Table 4

Response latency model estimates

Task	Predictor	b	SE	t	p
LDT	Unrelated - Nonword	246.80	24.20	10.20	< .001
LDT	Unrelated - Semantic	-13.89	28.78	-0.48	.629
LDT	Unrelated - Associative	-96.63	28.62	-3.38	.001
LDT	Nonword - Semantic	-260.69	29.32	-8.89	< .001
LDT	Nonword - Associative	-343.43	29.15	-11.78	< .001
LDT	Semantic - Associative	-82.74	33.06	-2.50	.012
LST	Unrelated - Nonword	134.48	32.95	4.08	< .001
LST	Unrelated - Semantic	-201.81	39.48	-5.11	< .001
LST	Unrelated - Associative	-122.49	39.48	-3.10	.002
LST	Nonword - Semantic	-336.29	39.71	-8.47	< .001
LST	Nonword - Associative	-256.98	39.71	-6.47	< .001
LST	Semantic - Associative	79.31	45.28	1.75	.080

Note. Degrees of freedom are 2747 for lexical decision tasks and
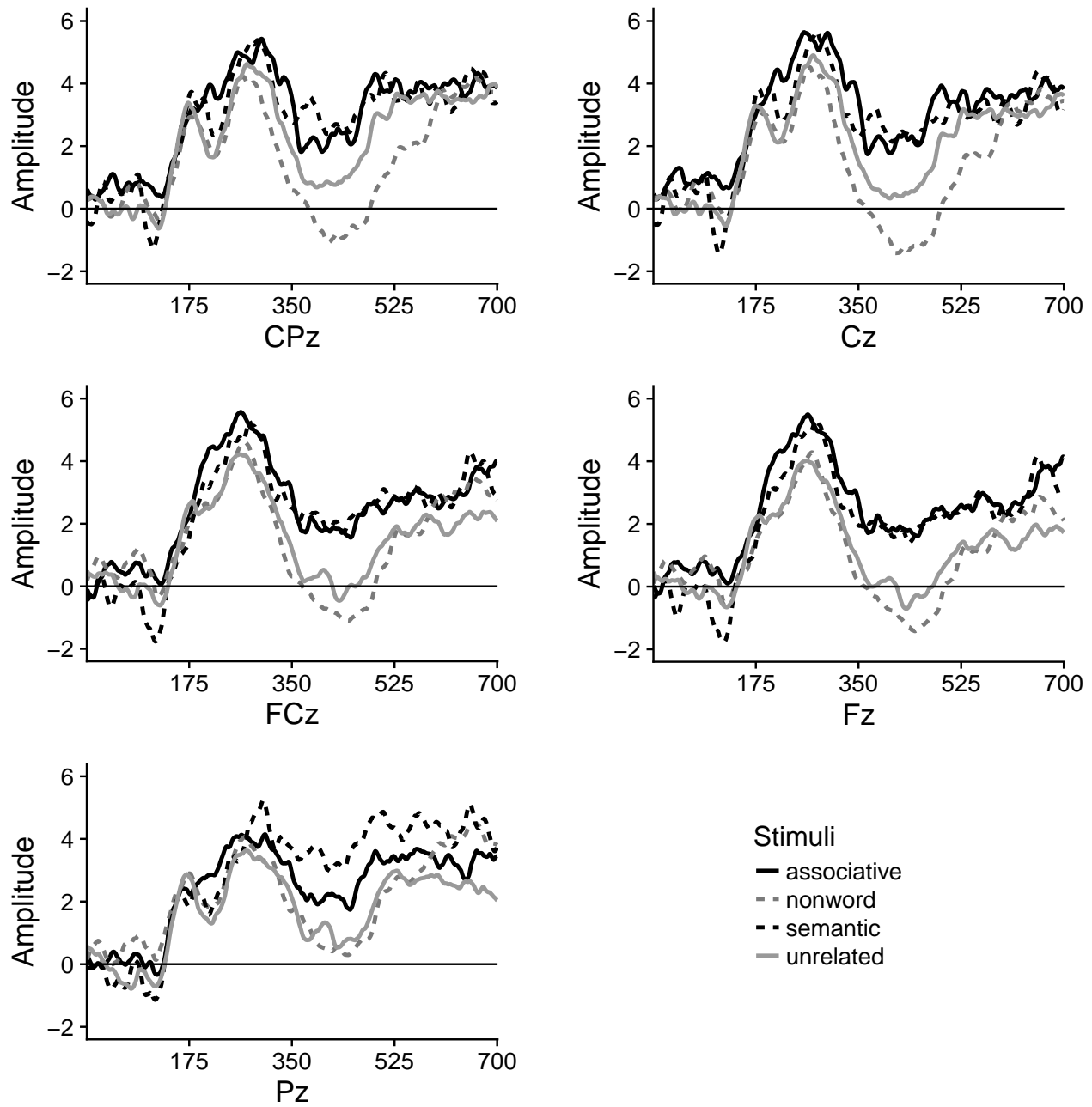
2753 for letter search tasks.
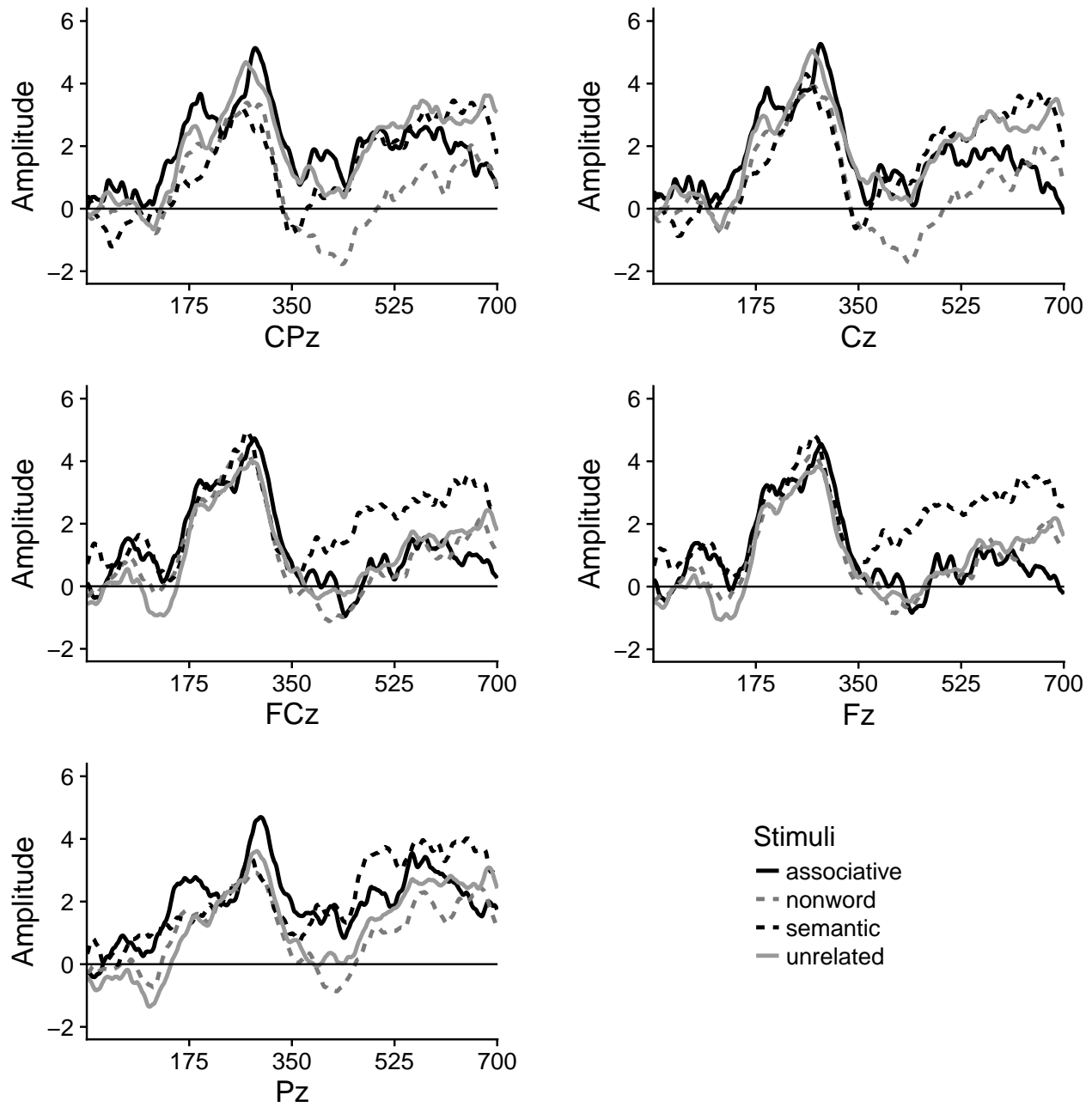
Figure 1. SOMETHING SOMETHING HERE
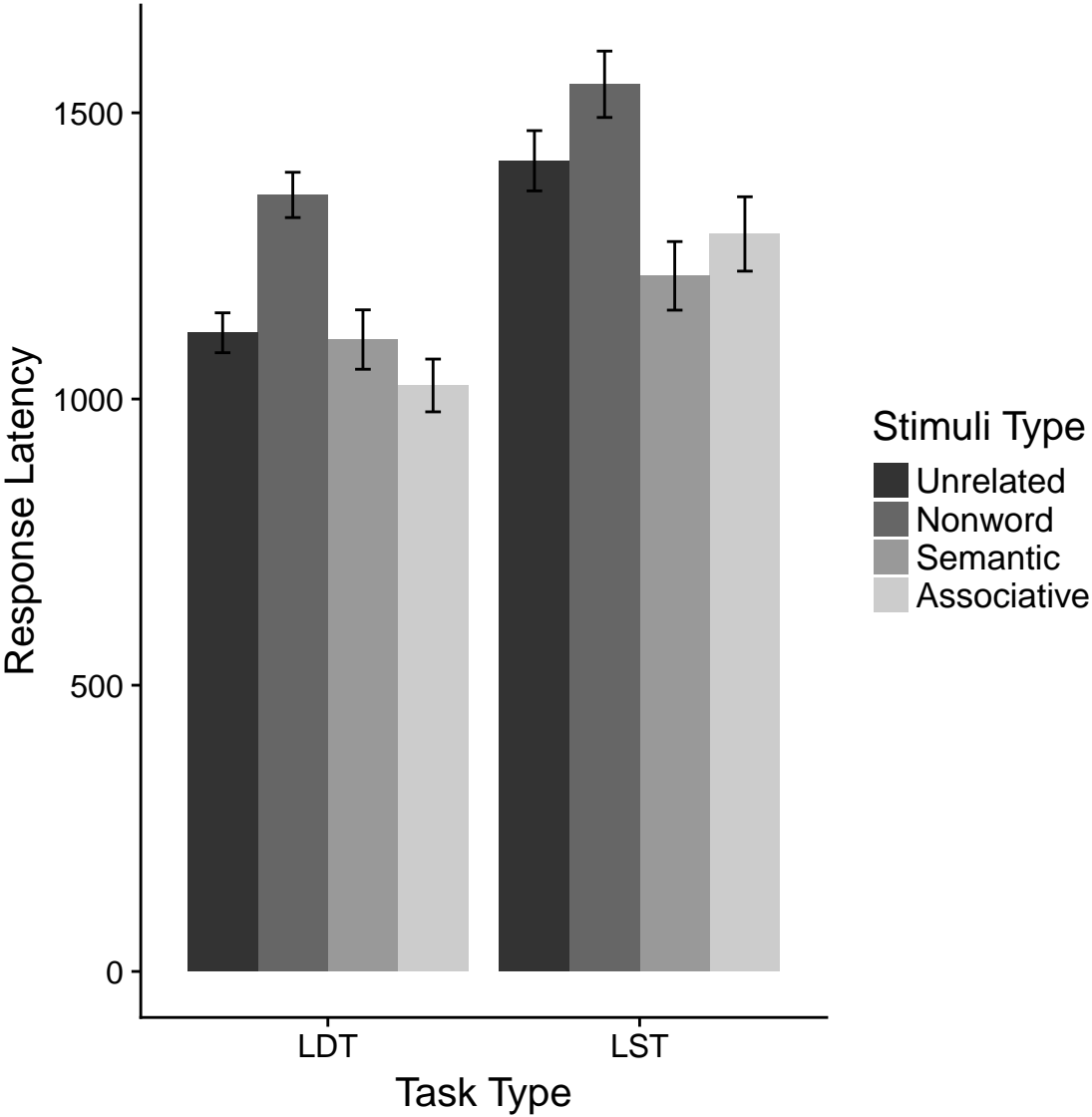
Figure 2. SOMETHING SOMETHING HERE

Figure 3. SOMETHING SOMETHING HERE