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 for the lexical decision task,

₂₀ indicating automatic access for both types of relatedness. For a letter search task, the N400

₂₁ showed differences between nonwords and other stimuli but no attenuation for related pairs.

₂₂ Response latency data indicated associative priming in both tasks with semantic priming

₂₃ also found in the letter search task. These results help discern possible automatic and

₂₄ controlled processes occuring during these tasks, as the N400 may show automatic processing

₂₅ during the lexical decision task, while the response latency data may provide evidence for

₂₆ controlled processing during the letter search task.

₂₇   *Keywords:* association, semantics, priming, N400, EEG, lexical decision, letter search

₂₈ The N400's 3 As: Association, Automaticity, Attenuation (and Some Semantics Too)

₂₉ Semantic facilitation through priming occurs when a related cue word speeds the

₃₀ processing of a following target word (Meyer & Schvaneveldt, 1971). For example, if a person

₃₁ is reading about a yacht race, the word boat is easier to process because of previous

₃₂ activation in semantic memory. Research suggests that priming transpires by both automatic

₃₃ and controlled processes. The automatic model proposes that related words are linked in the

₃₄ brain due to overlapping features (Collins & Loftus, 1975). Target words are activated

₃₅ without conscious control due to automatic spreading activation within related cognitive

₃₆ networks. Lexical and feature networks are thought to be stored separately, so that semantic

₃₇ priming is the activation from the feature network feeding back into the lexical level (Stolz &

₃₈ Besner, 1996). The overlap of a second word's semantic relatedness makes word recognition

₃₉ easier because it, in essence, has already been processed. The controlled process model

₄₀ proposes that people actively use cognitive strategies to connect related words together.

₄₁ Neely (1991) describes both expectancy generation and post lexical matching as ways that

₄₂ target word processing may be speeded. In expectancy generation, people consciously

₄₃ attempt to predict the words and ideas that will appear next, especially in sentences.

₄₄ Whereas in post lexical matching, people delay processing of the second target word so that

₄₅ it can be compared to the cue word for evaluation. In both cases, the target word is

₄₆ quickened by its relationship to the cue word.

₄₇ Traditionally, priming has been tested with a simple word or nonword decision called a

₄₈ lexical decision task. Participants are shown a cue or priming word, followed by a related or

₄₉ unrelated target word for the word/nonword judgment. Priming occurs when the judgment

₅₀ for the target is speeded for related pairs over unrelated pairs. Lexical decision tasks have

₅₁ been criticized for their inability to distinguish between automatic and controlled processing,

₅₂ so both single presentation lexical decision tasks and masked priming manipulations have

₅₃ been introduced to negate controlled processing (Ford, 1983). In a single lexical decision

₅₄ task, participants assess both the cue and target word so that they are not as overtly paired

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

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

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

Priming in the Brain

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

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

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

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

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

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

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

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

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

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

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

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

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

72 meanings are already activated.

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

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

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

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

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

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

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

80 transpires with semantic information from multi-word characteristic representations

(Hagoort, Baggio, & Willems, 2009; Kutas & Federmeier, 2011). This condition supposedly rules out automatic processes, because the masked prime condition only allowed automatic processes to take place. Masked priming did not allow the participants to consciously name the prime words they had seen; thus, they were not able to purposefully employ conscious cognitive strategies in processing these words. However, Deacon, Hewitt, Yang, and Nagata (2000) have found that with shorter stimulus onset asynchronies (SOAs), this effect of masked priming disappears. SOAs are the time interval between the prime word presentation and the target word appearance. Short SOAs are thought to only allow for automatic processing because the controlled, attention based processing has not had time yet to occur. Their study showed the masked primes long enough to enhance priming, while remaining imperceptible. With these modifications, Deacon, Dynowska, Ritter, and Grose-Fifer (2004) found equal N400 attenuation for the masked and unmasked primes. This result would indicate that automatic activation was taking place, as the masked prime condition did not allow controlled processes to take place. Kiefer (2002) has found similar results in the N400 using different masking levels, which kept judgment ability of prime words below chance.

A separate theory suggests that N400 effects are seen pre-word recognition. The N400 was found to be sensitive to pseudo- or nonwords, even when absent a resemblance to real word counterparts. Deacon et al. (2004) explain that this result could imply processes that precede word recognition, such as orthographic or phonological analysis. More recently, Federmeier and Laszlo (2009) suggested that the N400 indexes access to semantic memory. Meaningful stimuli representing a multitude of modalities indicates a sensitivity with attention, albeit still can occur in its absence. Processing from modalities can integrate, yielding different meanings from different contexts, respectively (Federmeier & Laszlo, 2009). Regardless of competing aspects as to what the N400 is estimated to index, vital insights have been made crossing different cognitive domains, with the N400 illuminating aspects originating from these different domains (Kutas & Federmeier, 2011).

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

150 **Separating Semantic and Associative Priming**

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

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

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

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

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

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

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

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

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

160   research centering on distinctions between associative and semantic priming.

161   With the databases described above, orthogonal word pair stimuli can be created to

162   examine associative and semantic priming individually and indeed, priming can be found for

163   each relation separately (Buchanan, 2010). Few studies have directly compared associative

164   and semantic relationships, especially focusing on the brain. Deacon et al. (2004) claim that

165   hemispheric differences exist in lexico-semantic representation, comparing associative and

166   semantic priming. Deacon et al. concluded that semantic features are localized in the right

167   hemisphere, whereas association is localized more within the left hemisphere of the brain.

168   The current study, with an aim to elaborate on basic theoretical questions such as the

169   relationship between associative and semantic processing, examined the relationship between

170   N400 activation, priming task, and word relationship type. Participants were given both a

171   single lexical decision and letter search task, along with separate semantic, associative, and

172   unrelated word pairs. We expected that the N400 modulation might vary from the different

173   types of word relation, which would indicate differences in cognitive processing and word

174   organization.

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Method

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Participants

177   Twenty undergraduate students were recruited from the University of Mississippi

178   (thirteen women and seven men), and all volunteered to participate. All participants were

179   English speakers. The experiment was carried out with the permission of the University's

180   Institutional Review Board, and all participants signed corresponding consent forms. One

181   participant's EEG data was corrupted and could not be used, and another participant was

182   excluded for poor task performance (below chance), leaving eighteen participants (twelve

183   women and six men).

EEG Acquisition

The system used was a 32 Channel EEG Quik-Cap (https://compumedicsneuroscan.com/product/32-channels-quik-cap/) connected to a NuAmps monopolar digital amplifier (https://compumedicsneuroscan.com/product/nuamps-40-channel-eeg-erp-amplifier/), which was connected to a computer running SCAN 4.5 software to record the data. The Quik-Cap includes Ag/AgCl sintered ring electrodes and the layout follows the International 10/20 system with the following sites: F7, FT7, T7, TP7, P7, FP1, F3, FC3, C3, CP3, P3, O1, Fz, FCz, Cz, CPz, Pz, Oz, FP2, F4, FC4, C4, CP4, P4, O2, F8, FT8, T8, TP8, and P8. The ground electrode was embedded in the cab at FPz, and two elecctrodes were attached to the mastoid bones.

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 (https://compumedicsneuroscan.com/product/stim2-precise-stimulus-presentation/). 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 continuously by the SCAN software. At the start of th experiment, adjustments were made until impedance values were below 5 kΩ. Data processing is described below.

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),

210 associatively related to the prime (60), or were nonwords (120). We used only a small

211 number of related word pairs to try to reduce expectancy effects described in the

212 introduction (Neely, 1991). These 360 pairs were split evenly between the lexical decision

213 and letter search task, therefore, each task contained 60 unrelated pairs, 30 semantically

214 related pairs, 30 associatively related pairs, and 60 nonword pairings. The ratio of yes/no

215 correct answers for words and nonwords in the lexical decision task was 2:1 and 1:1 yes/no

216 decisions in the letter search task. Splitting the nonword pairs over both the letter search

217 and lexical decision task created a higher yes/no ratio for the lexical decision task, which was

218 controlled for by mixing both tasks together.

219   The stimuli were selected from the Nelson et al. (2004) associative word norms and

220 Maki et al. (2004) semantic word norms. The associative word pairs were chosen using the

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

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

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

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

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

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

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

228 1.58) and LST $M = 21.12$ ($SD = 1.77$). For semantic pairs, the JCN was low for both the

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

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

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

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

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

234 require that the participant process the word cognitively. Essentially, nonwords were

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

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

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

https://osf.io/h5sd6/, along with the markdown template used to create this paper (Aust &

Barth, 2017).

Procedure

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

decision was green). The experiment made use of six sets of 60 randomly assigned word pairs for a total of 360 trials. These trials were presented in Arial 19-point font, and the inter-trial interval was set to two seconds to allow complete recording of the N400 waveform. Trials were recorded in five minute blocks, and between blocks participants were allowed to rest to prevent fatigue. The current task differed from Smith and Besner (2001) in that participants responded to every word (prime and targets), instead of only targets. Therefore, there was no typical fixed stimulus onset asynchrony (SOA) because participant responses were self-paced.

Results

N400 Waveform Analysis

EEG Preparation. The data were cleared of artifact data using EEGLAB (http://sccn.ucsd.edu/eeglab/; Delorme & Makeig, 2004), an open source MATLAB tool for processing electrophysiological data. The program automatically scanned for and removed artifacts caused by eye-blinking using independent component analysis. 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.

Data Screening. 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.

Data Analytic Plan.   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

316 coded as a dummy variable. In this analysis, we wished to compare each stimulus type to

317 every other stimulus type, and therefore, we set α for these six comparisons to $.05/6 = .008$.

318 The stimuli variable was recoded to examine all pairwise comparisons.

319   **Area Under the Curve Results.** Table 1 includes the model statistics for the

320 lexical decision and letter search tasks examining area under the curve. Participants were

321 included as a random intercept factor, as this model was significantly better than an

322 intercept only model, $p < .001$. The addition of the predictors of site and type of stimulus

323 were also significant for both models, $p < .001$ and $p = .003$. Table 2 includes the estimates

324 for each pairwise comparison for word stimulus type. For the lexical decision task, we found

325 that nonwords and unrelated had significantly larger areas under the curve than related word

326 pairs. Nonwords and unrelated pairs were not different using our corrected α value. This

327 find replicated previous work that the N400 was larger for unexpected words, while related

328 word pairs showed attenuation. Semantic and associative stimuli did not show differences in

329 their area under the curve. Figure 1 displays the ERP waveforms, separated by site, for the

330 lexical decision task. For the letter search task, a similar pattern emerges for nonwords, in

331 that they showed larger areas under the curve than all other stimuli. However, we did not

332 find attenuation for related words, as unrelated, semantic, and associative words showed the

333 same area under the curve in this task. Figure 2 portrays the letter search task. The two

334 gray lines represent unrelated and nonwords, which have larger areas under the curve than

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

336 **Task Performance**

337   **Data Screening.** One persons data was corrupt for the complete task component,

338 and one participant's task excluded several of their responses. The missing responses were

339 excluded for this analysis ($n = 16$ complete with 360 responses, $n = 1$ with 329 responses).

340 Task data were scored for correctness in the two tasks, and overall performance was around

341 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.

Response Latency Results.   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 the N400 area under the curve, we found priming for both semantic and associative word pairs in the letter search task. Nonwords were again slower than all other stimuli types, followed by unrelated word pairs. Again, semantic and associative pairs were not different. These analyses were examined with the outliers included in the analysis, as we considered that eliminating 214 trials may have skewed the results. The pattern of results did not change, but the differences between unrelated pairs and other stimuli types do become larger.

Discussion

These experiments were designed to explore the differences between N400 activation in the brain following presentation of semantic-only, associative-only, and unrelated word pairs in priming tasks. The N400 data presented a picture of semantic and associative

attenuation in comparison to nonword and unrelated word pair stimuli for the lexical

decision task. In contrast, the letter search task showed larger area under the curve results

for the nonword stimuli, but no differences were found in the other stimuli pairs. The task

data somewhat contradicted these results, as priming was found for associative word pairs

only in the lexical decision task, while the letter search task showed both associative and

semantic priming. It is possible that the task data were mixed because of the stimuli chosen,

even though these were controlled as best as possible with avaliable semantic and associative

databases. As Hutchison (2003) points out, associatively related items often tend to be

semantically related, and norming tasks may miss some associations due to sampling.

Additionally, as seen in Figure 3, the response latencies in this study are long,

especially compared to the typical values found in the English Lexicon Project (Balota et al.,

2007). The longer response times are likely due to task demands switching between lexical

decision and letter search tasks, and these results are similar to Smith and Besner (2001).

We did not replicate their findings for the letter search task, as we found both semantic and

associative priming. These differences could be due to stimuli, prime type (i.e., our

participants judged both target and prime), or SOA, as potentially their results only replicate

at quick SOAs focused on semantic word pairs. Our experiment does expand their study by

using database normed stimuli, while also expanding to semantic and associative stimuli.

These results suggest a mix of automatic and controlled processing during a demanding

task-switching experiment. Although Deacon et al. (2000) and Deacon et al. (2004) point to

potential issues of the N400 and automaticity versus controlled processing, our results may

indicate the automatic processing of primed words over unrelated and nonwords when the

focus is on the word reading level (i.e., the lexical decision task). In the letter search task,

the focus on the orthographic or letter level may impeed the automatic processing, as viewed

through an Interactive Activation model of word reading (McClelland & Rumelhart, 1981;

Rumelhart & McClelland, 1982). There are sometimes dissociations between the N400 and

response latency 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).

Given the relatively long response latencies in our study, the task performance results may reflect controlled processing, especially post lexical matching (Neely, 1991). To date, research has focused on semantic priming and its automaticity without many controls for associative relationships embedded in word pairs. Therefore, our study does expand the smaller literature that focuses on separating these priming effects (Buchanan, 2010; Chiarello, Burgess, Richards, & Pollock, 1990; Perea & Gotor, 1997; Xavier Alario, Segui, & Ferrand, 2000). 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). Additionally, the Semantic Priming Project has illustrated that priming is extremely variable across stimuli ranging from decreases of 200+ msec to *increases* of over 300 msec with an average priming effect of ~25 msec (Hutchison et al., 2013).

Limitations do exist within these experiments. A larger sample size would increase the power coefficient of the findings, and this study's sample size was selected due to the convenience sampling and time demands for an undergraduate thesis project. 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 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
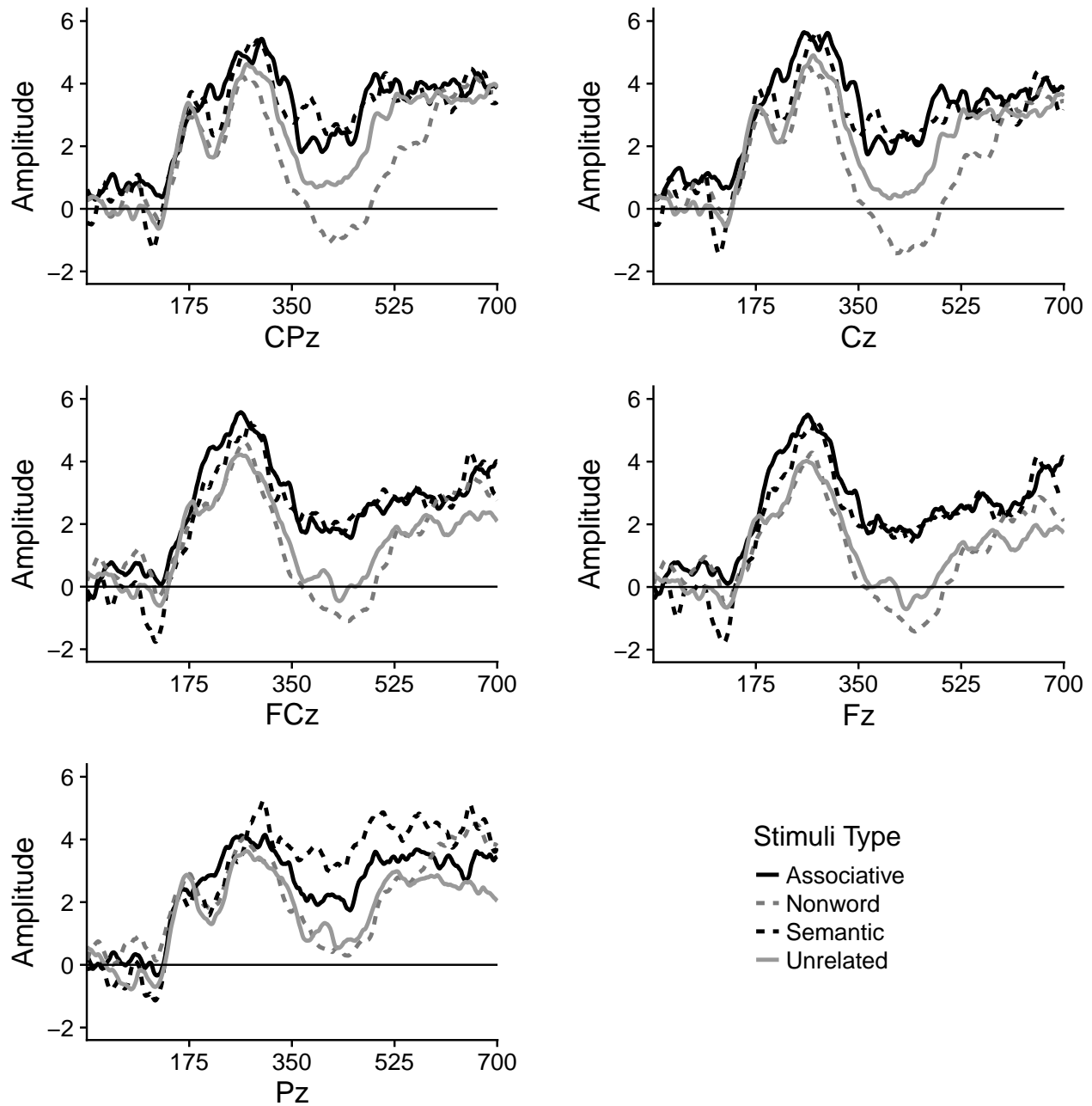2753 for letter search tasks.

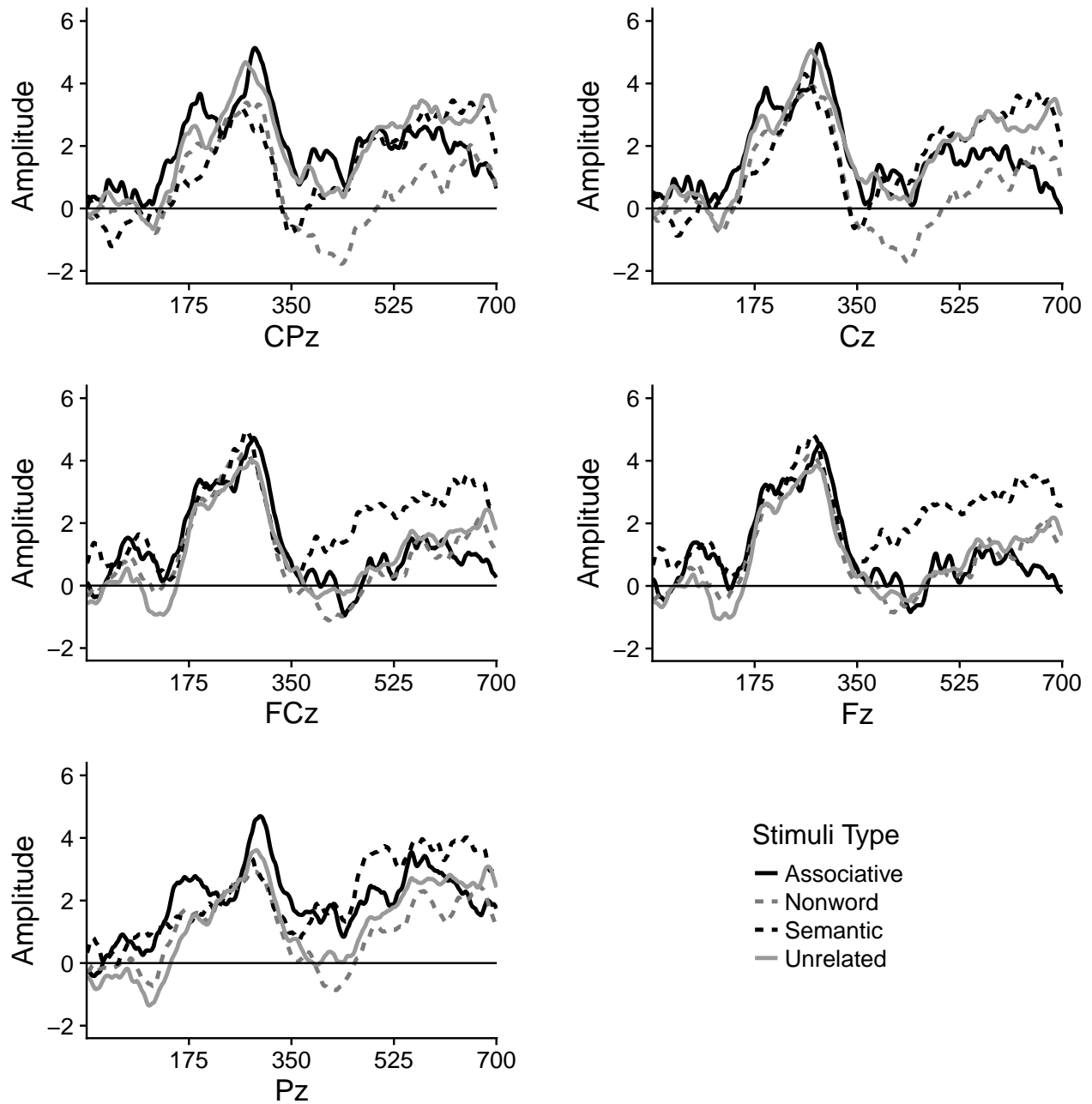*Figure 1*. EEG Waveforms for five midline sites for the four experimental stimuli in the lexical decision task.

Figure 2. EEG Waveforms for the letter search task across the five midline sites for each type of stimuli.
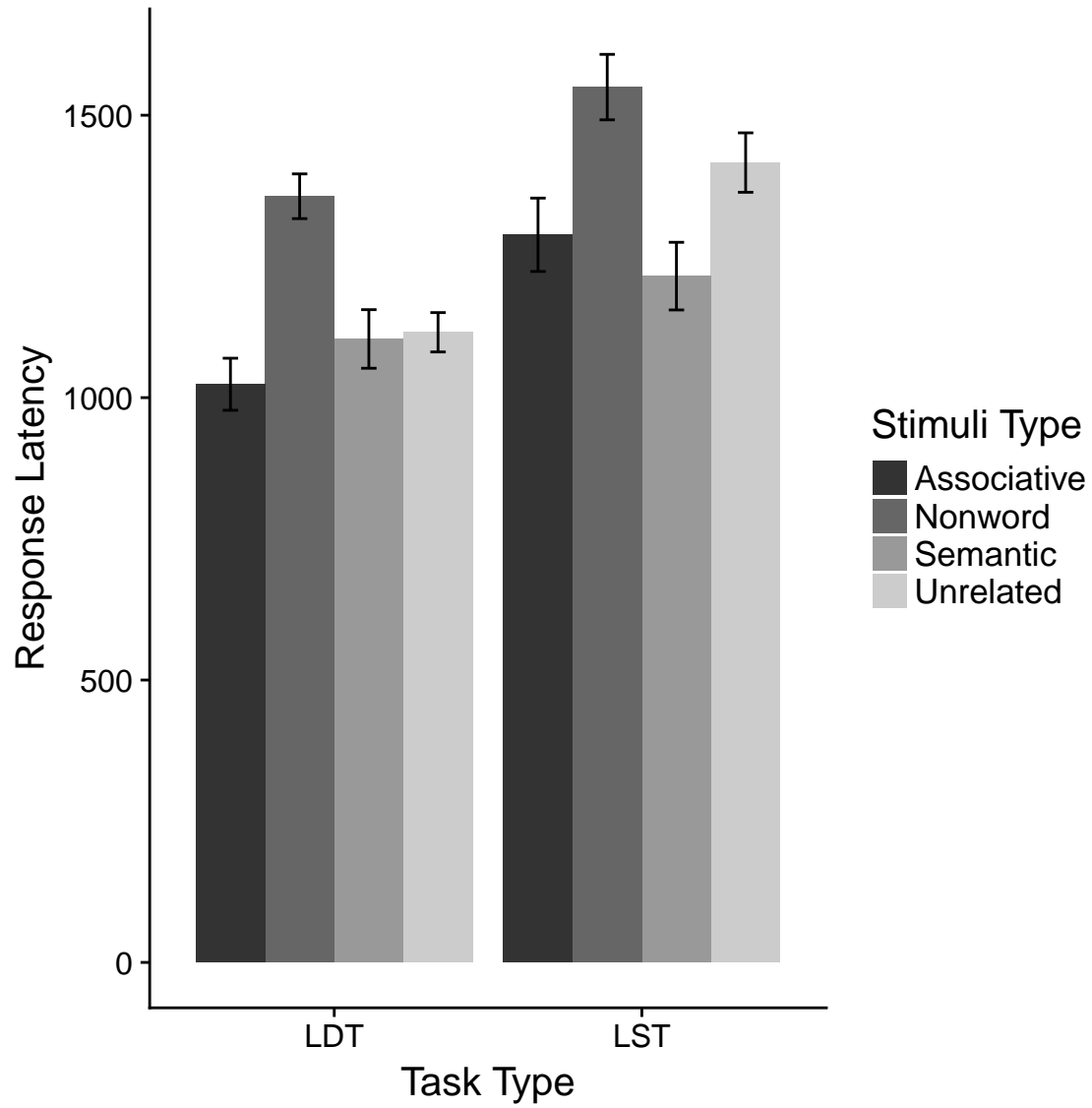
Figure 3. Response latency data for the lexical decision and letter search tasks for each stimuli type.