An ERP Investigation of Semantic Richness Dynamics:

Multidimensionality vs. Task Demands

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Abstract

Semantic richness is a multidimensional and dynamic construct that can be defined as the amount of semantic information a word possesses. In this thesis, the semantic richness dimensions of number of associates, number of semantic neighbours, and body-object interaction were investigated. Forty-eight young adults were randomly assigned to perform either lexical decision (LDT) or semantic categorization tasks (SCT). The goal of this thesis was to investigate behavioural and electrophysiological differences (using the Event-Related Potential technique) between semantically rich words and semantically impoverished words. Results revealed that the amplitude of the N400 ERP component was smaller for words with high number of associates and high number of semantic neighbours compared to words with low number of associates or low number of semantic neighbours, respectively, but only during LDT. Behavioural results, however, only showed an accuracy and reaction time advantage (during item analyses) for words with many associates. In contrast, N400 amplitudes did not differ for words with high body-object interaction rating when compared to words with low body-object interaction rating in any of the tasks, although a behavioural reaction time advantage was observed in item analyses of the LDT.

These results suggest that words with many associates or semantic neighbours may be processed more efficiently and be easier to integrate within the neural semantic network than words with few associates or semantic neighbours. In addition, the N400 effect was seen in the LDT but not in the SCT, suggesting that semantic richness information may be used in a top-down manner in order to fulfill the task requirements using available neural resources in a more efficient manner.

Résumé

La richesse sémantique est une construit multidimensionnel et dynamique qui peut être définie comme étant la quantité d'information sémantique qu'un mot possède. Dans cette thèse, ces dimensions de richesse sémantique ont été examinées : le nombre d'associés, le nombre de concepts sémantiques voisins et l'interaction corps-objet. Quarante-huit adultes jeunes ont été assignés de façon aléatoire à effectuer soit une tâche de décision lexicale (TDL) ou catégorisation sémantique (TCM). L'objectif de cette thèse était d'examiner les différences comportementales et électrophysiologiques (en utilisant la technique des potentiels évoqués, *event related potential* ; ERP) entre les mots riches et pauvres de façon sémantique. Les résultats ont révélé que l'amplitude de la composante ERP N400 était plus petite pour les mots avec un grand nombre d'associés et plus grande pour les mots avec un grand nombre de voisins sémantiques à comparer les mots avec un nombre faible de sens associés ou un nombre faible de voisins sémantiques, respectivement, mais seulement pendant la tâche de TDL. Les résultats comportementaux, toutefois, ont démontré un avantage à l'égard de l'exactitude et du temps de réaction (pendant l'analyse d'items) pour les mots avec un grand nombre d'associés seulement.

En contraste, les amplitudes de N400 ne différaient pas pour les mots avec une évaluation d'interaction corps et objet forte à comparer une évaluation d'interaction corps et objet faible lors de toutes les tâches, bien qu'un avantage sur le plan du temps de réaction ait été observé pour l'analyse d'items de la tâche TDL.

Ces résultats suggèrent que les mots avec un grand nombre d'associés ou de concepts sémantiques voisins peuvent être traités plus efficacement et plus facilement être intégrés dans le réseau sémantique neuronal que les mots avec peu de sens associés ou de concepts sémantiques voisins. De plus, les effets de la N400 ont été détectés pour la TDL, mais pas la TCM, suggérant

que la richesse sémantique de l’information peut être utilisée de façon *top-down* (descendante) dans l’objectif de répondre aux exigences d’une tâche en utilisant les ressources neuronales disponibles efficacement.

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Contribution of Authors

The experiments in this thesis were conceived by Rocío López Zunini, with guidance from Dr. Vanessa Taler. Rocío López Zunini selected the stimuli, designed the experiments, programmed the tasks, recruited and tested participants, and processed and analyzed the data under the supervision of Dr. Taler. Rocío López Zunini and Dr. Taler interpreted the results in collaboration. A manuscript for publication as a result of this thesis is currently under revision. The co-authors are Rocío López Zunini, Dr. Louis Renoult, and Dr. Vanessa Taler. Rocío López Zunini wrote the manuscript. Dr. Louis Renoult and Dr. Taler provided statistical advice and interpreted the results in collaboration with Rocío López Zunini.

Chapter 1: Introduction

1.1 Thesis Overview

Concepts and their meanings are vital for language comprehension and communication, and yet we still do not fully understand the complex process by which meaning is extracted from words. This process can be modulated by numerous variables as well as the context in which it occurs (Balota & Chumbley, 1984; Yap, Pexman, Wellsby, Hargreaves, & Huff, 2012; Yap, Tan, Pexman, & Hargreaves, 2011). In order to develop a comprehensive theory of how concepts are processed and how meaning is extracted from words, it is crucial to investigate the effects of variables known to influence language processing, as well as to compare these effects in different lexical and semantic contexts.

In recent years, a new construct referred to as semantic richness has received considerable attention (e.g., Pexman, Siakaluk, & Yap, 2013). Semantic richness refers to the amount of semantic information associated with a concept. Studies have shown that concepts that are semantically rich are processed faster and/or more accurately relative to concepts that are less semantically rich (Pexman, Hargreaves, Siakaluk, Bodner, & Pope, 2008; Siakaluk, Buchanan, & Westbury, 2003; Siakaluk, Pexman, Sears, et al., 2008; Yap et al., 2012). Behaviourally, this processing advantage has been shown to vary depending on the language task at hand (Yap et al., 2011), suggesting that the facilitatory effects of semantic richness are dynamic. However, the neurocognitive processes associated with such dynamics remain unclear. The topic of my thesis thus consisted of investigating the neurocognitive processes associated with semantic richness dynamics. For that, I used the Event-Related Potential (ERP) technique, a neuroimaging method with excellent temporal resolution. In addition, I chose two different language tasks: a lexical decision task (LDT) and a semantic categorization task (SCT). In an LDT, participants have to discriminate between a real word ("house") and a pseudo-word ("flirc") while in a SCT, participants are asked to classify words based on semantic categories (e.g., is "tiger" a living or a non-living entity?). In a LDT participants may rely more on familiarity-based information (e.g., word frequency, bigram frequency) than on semantic variables to discriminate a word from a pseudoword (Balota & Chumbley, 1984). In contrast, in a SCT, access to semantic information is an integral part of the decision making process. Therefore, comparing semantic effects in these two tasks constitutes an ideal scenario to investigate semantic richness dynamics.

Finally, semantic richness is a multidimensional construct that can be measured according to the different properties associated with concepts. In this thesis, three semantic richness dimensions and their interactions with task demands were investigated: number of associates (chapter 2), number of semantic neighbours (chapter 3), and body-object interaction (chapter 4). Before presenting the results of chapters 2 to 4, I provide a detailed literature review of the semantic richness dimensions mentioned above as well the state-of-the art of word recognition and cognitive electrophysiological research.

1.2 Visual Word Recognition

Word identification and access to word meaning has been largely investigated with visual word recognition tasks. Over the course of the years, several different tasks have been used in order to elucidate the role that variables play during lexical-semantic access (e.g., Balota, Cortese, Sergent-Marshall, Spieler, & Yap, 2004; Yap & Balota, 2007). One of the most widely used paradigms has been the visual lexical decision task (LDT) (James, 1975; Jastrzembski, 1981; Katz et al., 2012; Whaley, 1978). According to Balota and Chumbley (1984), to decide whether a word is real or not, participants access and discriminate information along the familiarity and the meaningfulness dimensions. In the familiarity dimension, information about the orthographic and phonological similarity to an internal representation of the word is available, whereas in the meaningfulness dimension information about the meaning of the word is accessed. Balota and Chumbley have demonstrated that both are necessary during the lexical decision process, but that familiarity-based information exerts a larger effect in these types of tasks than in other tasks such as category verification or naming.

In reading aloud or word naming, participants are asked to read the letter string presented as quickly and as accurately as possible. When compared to LDT, word naming has been shown to rely less on semantic information (Yap & Balota, 2009) because it requires the translation of an orthographic representation into a phonological one; thus, semantic information is less important although it can facilitate reading of low frequency words with irregular spelling-to-sound correspondences (Strain, Patterson, & Seidenberg, 1995).

Another visual word recognition paradigm is progressive demasking (PDM), which is a perceptual identification task where a word is rapidly alternated with a mask (e.g., ####) to then gradually become more visible after successive word-mask alternations. Participants are asked to make a decision as soon as they are able to identify the word. This task is thought to make more salient factors affecting early word recognition processes because it slows down the recognition process (Dufau, Stevens, & Grainger, 2008). However, PDM has been shown to produce similar effects as in the LDT and is mainly influenced by word length and the first letter of a word (Ferrand et al., 2011; Yap et al., 2012).

Finally, semantic categorization tasks (SCT) are another way to investigate word recognition processes. In a SCT, participants are required to classify words according to categories; thus, it is thought to rely more on semantic information than LDTs (Yap et al., 2012).

Commonly used SCTs include classifying words as concrete or abstract (Hargreaves & Pexman, 2014; Pexman et al., 2008), living or non-living (McRae, Cree, Seidenberg, & McNorgan, 2005; Mirman & Magnuson, 2008), or consumable or not consumable (Pexman, Hargreaves, Edwards, Henry, & Goodyear, 2007).

Lexical and semantic information influence performance in all the paradigms mentioned above. However, the influence of such information is largely dependent on the type of task (e.g., Balota et al., 2004). In this thesis, I am interested in the influence of a number of semantic variables and their interactions with the demands of the task. Thus, an ideal scenario would be to compare performance in two paradigms that are identical (in terms of stimulus presentation and motor response) but only differ in the type of decision to be made. Of the paradigms mentioned above, the LDT and SCT fulfill such criteria: they can be presented in an identical manner and can require the same motor response while differing only in the decision process. Thus, a comparison of performance in the two tasks would constitute an ideal scenario for investigating context-dependent word recognition processes.

1.3 Variables influencing Word Recognition Performance

1.3.1 Lexical variables. Lexical variables typically refer to the characteristics of a word that are above its individual phonemes or letters but below its semantic characteristics (Balota et al., 2004; Yap & Balota, 2009). Visual word recognition studies have shown that numerous lexical variables can influence task performance (Yap & Balota, 2015). Word frequency exerts the most ubiquitous effect, whereby high frequency words are recognized faster and more accurately than low frequency words (e.g., Andrews & Heathcote, 2001; Monsell, Doyle, &

Haggard, 1989), and can explain about 40% of the variance in LDTs and SCTs and about 10% in word naming (e.g., Balota et al., 2004; Yap et al., 2012).

Another important variable shown to influence word recognition is orthographic neighbourhood density (OND). An orthographic neighbour of a letter string is obtained by substituting one letter in a word with another (Coltheart, Davelaar, Jonasson, & Besner, 1977). Thus, for example, some neighbours of the word "bat" are "cat", "bit", and "bar". Words with many orthographic neighbours exert a facilitatory effect, whereby they are recognized faster than words with few orthographic neighbours during LDT, while pseudowords with many orthographic neighbours are recognized as non-words slower than pseudowords with few orthographic neighbours (e.g., Andrews, 1989). During SCTs results are less clear, with some studies finding a facilitatory effect (Sears, Lupker, & Hino, 1999) and others an inhibitory effect (Carreiras, Perea, & Grainger, 1997).

The familiarity of a word also plays a role in word recognition performance (Balota, Pilotti, & Cortese, 2001). Familiarity ratings are determined from questionnaires asking participants how familiar a concept is based on the frequency of experience with it. Research has shown that performance during LDT is also influenced by a word's familiarity, independent of objective frequency measures (Balota & Chumbley, 1984; Besner & Swan, 1982). More specifically, the facilitatory objective frequency effect in LDT reaction times is smaller when high and low frequency words are matched on measures of familiarity (Colombo, Pasini, & Balota, 2006).

Finally, word length also affects performance: 3-5 letter words exert a facilitatory effect, 5-8 letter words a null effect and longer words an inhibitory effect on reaction time during LDTs (New, Ferrand, Pallier, & Brysbaert, 2006).

1.3.2 Semantic variables. Early visual word recognition studies primarily concentrated on the effects that lexical variables exerted on performance. However, numerous studies have shown that semantic information also plays a role in word recognition processes (see Pexman et al., 2013). The seminal study by James (1975) was the first one to investigate the effects of semantic information during LDT. His findings demonstrated that word recognition was faster for low frequency concrete words than low frequency abstract words. Later studies showed that lexical decision times could be predicted by concreteness and imageability (Whaley, 1978), and number of senses (Jastrzembski, 1981). These earlier findings demonstrated that different types of semantic information contributed to word recognition and gave rise to a new construct, *semantic richness,* which refers to the amount of semantic information associated with a given word.

1.4 Semantic Richness

A number of studies have shown that words that are semantically rich (i.e., words that possess relatively more semantic information) are recognized faster and more accurately than words that are more semantically impoverished (e.g., Buchanan, Westbury, & Burgess, 2001; Duñabeitia, Aviles, & Carreiras, 2008; Pexman et al., 2008; Yap et al., 2011). Moreover, these effects have been shown across several dimensions (Yap et al., 2012; Yap et al., 2011). Semantic richness dimensions include imageability, number of features, number of senses, number of associates, semantic neighbourhood density (or number of semantic neighbours), and body-object interaction. More recent studies have included measures of semantic diversity, semantic information associated with survival such as avoiding death and locating nourishment, and danger and usefulness ratings.

As mentioned in the previous section, the first studies investigating the role of semantic information on word recognition measured differences in performance when identifying concrete/imageable words vs. abstract words. Imageability is defined as the ease with which a word evokes mental imagery (Paivio, Yuille, & Madigan, 1968). Imageability is measured by asking people to rate on a Likert scale how imageable a word is (e.g., Bennett, Burnett, Siakaluk, & Pexman, 2011; Paivio et al., 1968), and is highly correlated with concreteness (Paivio et al., 1968). For example, Bennett et al. asked participants to rate the ease or difficulty with which a list of words arouse mental imagery (e.g, a mental picture of a sound). As mentioned above, studies using lexical decision have found that concrete words are recognized faster than abstract words (James, 1975; Whaley, 1978). In addition, Balota et al. (2004) have shown that highly imageable words predicted reaction time and accuracy in a large set of words. Concreteness and imageability, however, are dissociable. For example, "opium" is a concrete noun that is low in imageability, whereas the noun "fun" is abstract but high in imageability. A behavioural advantage can be seen during free recall studies when remembering highly imageable words that are low in concreteness (Richardson, 1975). Furthermore, a recent study by Dellantonio, Mulatti, Pastore and Job (2014) has shown that while imageability ratings measure both external and internal sensory experience (e.g., emotion, proprioceptive and interoceptive information), concreteness relies primarily on external sensory experience. Thus, although a number of studies treated both variables as identical, it is important to control for both.

The semantic richness dimension "number of features" refers to the attributes or properties associated with a concept (McRae et al., 2005). The number of semantic features associated with a given concept is typically identified in studies where participants are asked to list the semantic features associated with a word (e.g., for the word "dog" these might be "it has four legs", "it barks", "it has fur"). Words with many semantic features are recognized more quickly than words with few semantic features in semantic categorization, lexical decision, and naming tasks (Pexman et al., 2008; Pexman, Lupker, & Hino, 2002).

Another semantic richness dimension is semantic ambiguity, which refers to words that have more than one meaning (e.g., "bank"). Several studies have found that ambiguous words are recognized faster than unambiguous words during lexical decision (Borowsky & Masson, 1996; Ferraro & Hansen, 2002; Hino, Lupker, & Pexman, 2002; Hino, Pexman, & Lupker, 2006; Kellas, Ferraro, & Simpson, 1988). However, there is evidence of a dissociation between the behavioural effects of ambiguous words with unrelated meanings vs. ambiguous words with related meanings (also referred to as words with related senses or polysemous words) (Klepousniotou & Baum, 2007; Rodd, Gaskell, & Marslen-Wilson, 2002). A concept is considered to have two or more related senses when its meaning changes according to the context in which it is used. For example, the word "vest" has many related senses (e.g., undergarment, life vest, bullet-proof vest) while the word "piano", refers only to a musical instrument. In contrast, a word like "bark" can have two unrelated meanings (also referred to as homonyms). For example, "bark" can be used to refer to the sound made by a dog or to a tree bark; in this case, the two meanings are completely unrelated.

Rodd et al. (2002) found that words with many unrelated meanings were recognized more slowly than unambiguous words during lexical decision, while words with many related senses were recognized more quickly than words with few senses. By contrast, an ambiguity disadvantage has been observed in living/non-living semantic categorization tasks (Hino et al., 2002). However, in this study homonymous and polysemous words were collapsed in the experiment, and the effects of ambiguity thus remain to be clarified.

Another similar but distinct dimension is semantic diversity, which estimates the degree to which the different contexts in which a word appears vary in their meanings (Hoffman, Lambon Ralph, & Rogers, 2013). According to Hoffman and colleagues, this measure provides more fine-grained information than a word's number of senses because there are words that have only one sense (i.e., are typically considered unambiguous), but are used in a variety of contexts. For example, the word "perjury" occurs in very similar contexts while the word "knowledge" has a more diverse context (Hoffman et al., 2013). More specifically, "perjury" is restricted to contexts related to the legal system, whereas "knowledge" can be used in many contexts, such as academic (e.g., "Her knowledge of biology was extensive") or everyday life (e.g., "I had no knowledge of her situation"). Thus, from a word such as "knowledge", one cannot infer very much about the situation in which the word was used without additional contextual information. Word recognition studies have found that words high in semantic diversity were recognized faster than words low in semantic diversity during lexical decision (Hoffman & Woollams, 2015). However, a reaction time disadvantage was observed during a semantic relatedness judgement task for high versus low semantic diversity words (Hoffman & Woollams, 2015).

Research by Amsel, Urbach and Kutas (2012) has identified two additional semantic richness dimensions associated with concrete nouns: avoiding death and locating nourishment. Amsel et al. asked participants to rate concrete nouns along a series of sensorimotor attributes that included likelihood of pain, taste pleasantness, smell intensity, graspability, sound intensity, visual motion and colour vividness. They then identified the two dimensions mentioned above using principal component analysis. In addition, they showed that along with certain types of features (derived from McRae et al.'s number of features norms) words associated with more intense smell were classified faster than words associated with less intense smell during a concreteness SCT, whereas words with higher likelihood of visual motion and increased taste pleasantness were recognized more quickly than words lower in those ratings during LDT.

In a similar vein, Wurm and Vacoch (2000) collected rating for two dimensions associated with survival: danger and usefulness. Their findings revealed an interaction of the two dimensions, whereby words low in usefulness and high in danger predicted faster reaction time, whereas those high in usefulness and high in danger predicted an inhibitory effect (Wurm, Vakoch, Seaman, & Buchanan, 2004). Although they did not interpret the interaction, they offered an account of the reaction time effects within the embodied cognition approach, whereby our experiences in the physical world (e.g., sensory experience and motor actions) influence cognitive processes, including language (Barsalou, 2008).

In sum, semantic richness dimensions influence word recognition performance. Facilitatory or inhibitory reaction time effects can be observed depending on the nature of the semantic information and the requirements of the task. In lexical decision tasks, facilitatory reaction time effects associated with a range of semantic richness dimensions have been observed. These dimensions include imageability, number of features, lexical ambiguity, semantic diversity, and danger and usefulness. In addition, while the facilitatory effects associated with a particular dimension seem to be extended to other language tasks (e.g., number of features), other dimensions such as lexical ambiguity and semantic diversity seem to exert an inhibitory effect in tasks that require deep semantic processing such as semantic categorization or semantic relatedness judgement. The following sub-sections will discuss the three semantic richness dimensions chosen for investigation in this thesis.

1.4.1 Number of associates. Number of associates (NA) is often defined as the number of first associates produced in a free association task (Nelson, McEvoy, & Schreiber, 1998). This variable was first quantified in a norming study by asking participants to provide the first word that came to mind after given a target word. Later, the number of responses was counted per target word (excluding responses given only by a single participant), thus providing a NA count that reflected the diversity of responses provided across participants. NA has been used to investigate memory (Nelson, Schreiber, & McEvoy, 1992) as well as word recognition processes (e.g., Balota et al., 2004; Buchanan et al., 2001).

In memory studies using recall tasks, NA has been found to have differential effects on performance as a function of the context in which the words are encoded or tested. Facilitatory effects are observed during free and cued recall for words with high NA that are encoded in the presence of unrelated words, whereas inhibitory effects are observed when the encoded words are tested in the presence of related words or when the study list contains items from the same category (e.g., Nelson, McEvoy, & Schreiber, 1990). These results show that NA memory effects are dynamic and they depend on the learning and testing environment.

During visual word recognition, words with many associates are recognized faster than words with few associates in lexical decision tasks (Balota et al., 2004; Buchanan et al., 2001; Duñabeitia et al., 2008; Locker, Simpson, & Yates, 2003; Yates, Locker, & Simpson, 2003). However, a study that used hierarchical regression analyses on lexical and several semantic richness variables found that NA effects did not predict performance in lexical decision or semantic categorization tasks when other semantic richness dimensions were accounted for (Yap et al., 2011). Finally, in an fMRI study by Pexman et al. (2007) where participants performed a semantic categorization task, words with many associates exhibited less activation in the left inferior frontal and temporal gyri than words with few associates, suggesting that words with many associates require less effort and less extensive semantic processing than those with few associates.

1.4.2 Semantic neighbours. Semantic neighbours can be quantified according to two different views: the object-based view or the language-based view. In the object-based view, semantic information is quantified using the properties of the object that a word refers to (Buchanan et al., 2001). For example, concepts like “rat” and “mouse” would be considered semantic neighbours because they share many semantic features (e.g., they are furry, have a tail, they are four legged, etc.) or because they belong to the same category (e.g., they are both animals, they are both rodents, etc).

In the language-based view, semantic neighbours are defined according to concepts’ statistical co-ocurrence in samples of text corpora. Thus, unlike in the object-based view, where two concepts would be neighbours because they share features, in association or co-occurrence models, concepts like “cow” and “milk” would be associated because they appear in similar contexts in large samples of corpus text (Burgess & Lund, 2000). Thus, words with high number of semantic neighbours (NSN) share lexical contexts with many other words, whereas the opposite applies for words with low NSN. According to Buchanan et al. (2001), semantic information derived from the language-based view has the advantage of identifying neighbours that are semantically related but that do not necessarily shared features, thus providing a more comprehensive measure of semantic neighbourhood. Thus, NSN defined according to the language-based view was investigated in this thesis.

Language-based view measures can be derived from mathematical analyses of large corpus of text where words are considered vectors in a high-dimensional space (e.g., Lund & Burgess, 1996; Shaoul & Westbury, 2010). One of the most prevalent models is the Hyperspace Analogue to Language (HAL) model (Lund & Burgess, 1996). The HAL model uses word co-occurrence to construct a vector space that contains contextual information for every word in a sample of text. The model quantifies words' co-occurrence within a radius of 10 words. More specifically, in a sample of text, words that are adjacent to the target word receive a value of 10, words that are separated from the target word by one other word receive a value of nine, and so forth until words that are separated by nine other words from the target word receive a value of one. A matrix is created for each word where words are represented as vectors in semantic space. The relative distance between words reflects their meaning similarity. The components of the word's vectors are calculated based on the number of times word pairs co-occur. Similar vectors are considered close neighbours in semantic space.

One problem with the HAL model is that high frequency context words (e.g., "the", "of", "from") bias the calculation of semantic distance (Shaoul & Westbury, 2010). An improved measure that is free from frequency bias is the "Windsor improved norms of distance and similarity of representations of semantics" (WINDSORS), which uses the same vector procedure as in the HAL model but applies two mathematical methods to eliminate the effects of word frequency (details can be found in Durda & Buchanan, 2008). Given its advantage over the HAL model, this thesis employed the measures from this model to explore the effects of semantic neighbourhood on word recognition.

Behavioural studies that quantified semantic neighbourhood according to the language-based view have found that words with large neighborhoods are processed more quickly and accurately than words with small neighbourhoods. This facilitatory effect has been found in lexical decision (Buchanan et al., 2001; Pexman et al., 2008; Yap et al., 2012; Yap et al., 2011) and naming tasks (Buchanan et al., 2001). However, the effects in semantic categorization tasks are not consistent. Mirman and Magnuson (2008) found that some measures of semantic neighbourhood were positively correlated with reaction time and accuracy in a living non-living semantic categorization task, while Siakaluk, Buchanan and Westbury (2003) found an effect when participants only had to respond to the target item (go/nogo semantic categorization) but not if they had to respond with a yes/no answer. Finally, regression analyses studies did not predict reaction time in semantic categorization tasks when other variables were accounted for (Pexman et al., 2008; Yap et al., 2012; Yap et al., 2011).

1.4.3 Body-object interaction. This semantic richness variable (BOI for short) refers to the ease with which a human can physically interact with an object. It has been quantified by Siakaluk and colleagues in studies where participants are asked to rate on a scale from 1 to 7 how much they can physically interact with a given object (Bennett et al., 2011; Tillotson, Siakaluk, & Pexman, 2008). In the visual word recognition literature, high BOI rating facilitates recognition: high BOI words (e.g.,"helmet") are processed more quickly and accurately than low BOI words (e.g., "statue") in lexical decisions and certain types of semantic categorization tasks such as imageable/not imageable decision tasks (Bennett et al., 2011; Siakaluk, Pexman, Aguilera, Owen, & Sears, 2008; Siakaluk, Pexman, Sears, et al., 2008; Tillotson et al., 2008; Wellsby, Siakaluk, Owen, & Pexman, 2011; Yap et al., 2012).

The BOI facilitatory effects reported in the literature are in line with Perceptual Symbol System (PSS) theory (Barsalou, 1999, 2003; Barsalou, Kyle Simmons, Barbey, & Wilson, 2003).

PSS theory proposes that concepts are formed and processed in a modality-specific manner; they then eventually pass on to hierarchical association areas where integration of information takes place (Damasio, 1989; LeDoux, 2001). These modalities are thought to be fundamental for acquiring and integrating knowledge; they include cognitive (e.g., attention), sensory (e.g., vision, audition), motor (e.g., grasping), kinesthetic (e.g., tactile, visceral or proprioceptive sensations), and emotional (e.g., anger, happiness) systems. When a concept needs to be retrieved, the different modalities that came into play when forming the concept are partially reactivated. In other words, a re-enactment or simulation occurs and they provide the cognitive representation that supports the concept in memory, language and thought. Thus, high BOI words may be processed more quickly and accurately than words with lower BOI ratings because they have relatively more sensorimotor information associated with them. This hypothesis is supported by Hargreaves et al.'s fMRI study (2012), which found that high BOI words were associated with more activation than low BOI words in the left supramarginal gyrus in the parietal lobule, an area thought to be involved with goal-oriented hand-object interaction.

1.5 Semantic Richness and its Dynamics with Language

A classical view of conceptual knowledge holds that concepts are stable and situationally invariant (''conceptual stability'') (Collins & Loftus, 1975; Fodor, 1975). More specifically, processing a concept involves the activation of a fixed set of properties; this process cannot be modified by task demands and is context-independent. However, recent studies have found that performance with concepts that are semantically rich can differ according to the demands of the task and can be context-dependent (Pexman et al., 2008; Tousignant & Pexman, 2012; Yap et al., 2011). More specifically, a semantic richness variable can influence performance in different ways depending on the type of task participants are asked to perform or the type of decisions they are asked to make (Yap et al., 2012; Yap et al., 2011). For example, words with many semantic neighbours are recognized faster than words with few neighbours during LDT but may have not have an effect during SCT (Yap et al., 2012). Similarly, body-object interaction effects differ as a function of task instructions (Tousignant & Pexman, 2012). Participants in Tousignant and Pexman were randomly assigned to perform word recognition tasks that used the same set of high and low BOI nouns (which they referred to as "entity words") but varied in the instructions given before each experiment began. In addition, the set of stimuli was also comprised of action words that had no BOI rating. In one experiment, they were asked to identify whether the words represented an entity or not (i.e., entity vs. non-entity decision), in another experiment they were asked whether the words represented an entity or an action (i.e., entity vs. action decision), and in a third experiment they were asked whether the words represented an action (i.e., action vs. non-action decision). A facilitatory effect was found only in the experiments where participants were explicitly told about entity words; that is the effect was only found when words with BOI rating were the focus in the decision making process. No facilitatory effect for high BOI words was detected in the experiment where participants were told to identify action words. These results suggest that participants exert top-down control based on the context information they receive. Information about a language task influences the participants to focus on semantic richness information that is relevant to the task.

These findings are in favour of theories assuming that concepts are flexible. According to this perspective, concepts are comprised of dynamical properties that can be context-dependent (Hoenig, Sim, Bochev, Herrnberger, & Kiefer, 2008; Kiefer & Pulvermuller, 2012). The notion that concepts are flexible implies that semantic richness effects observed in only one type of task cannot provide a full picture about the nature of semantic representations. Semantic richness dimensions that are important in one task may not be important in others. Depending on task demands, some dimensions might be emphasized at the expense of others, suggesting that meaning is dynamically shaped.

During word recognition, Balota and Yap (2006) put forward the notion of a *flexible lexical processor,* which states that attentional control is directed to language processes (e.g., orthographic, phonological, semantic) that are pertinent to perform a task. Empirical evidence supporting this notion shows that while lexical decision is mainly driven by familiarity and meaning, naming is driven by length, orthographic neighbourhood size and spelling-to-sound consistency (Balota et al., 2004), suggesting that participants engaged different language processes depending on the demands of the task. Similarly, the diverse behavioural effects that semantic richness dimensions exert on visual word recognition can be interpreted within this framework. However, much remains to be understood about the temporal brain dynamics associated with semantic richness and its interaction with task demands. In order to increase our understanding of this dynamic process, this thesis explored the effects of number of associates, number of semantic neighbours and body-object interaction on two different types of tasks that only vary in the type of decision to be made: a lexical decision task (LDT) and a semantic categorization task (SCT). In this thesis, I employed the Event-Related Potential technique, which due to its excellent temporal resolution allows one to study brain activity in real time. The following section reviews the different Event-Related Potential components associated with language and semantic richness effects.

1.6 Event Related Potentials and Visual Word Recognition

Reading occurs at an incredibly fast rate, with individual words being recognized in approximately half a second. Thus, Event-Related Potentials (ERPs) are an ideal technique to study the continuous online brain activity associated with recognizing words. ERPs are derived from the electroencephalogram and reflect the synchronous firing of post-synaptic potentials in large groups of pyramidal neurons in the neocortex. ERPs are characterized by positive or negative wave deflections that occur at a given time post-stimulus onset. Thus, they are named based on their polarity (positive or negative) and latency. For example, an N100 ERP component would be a wave with a negative deflection peaking at approximately 100 milliseconds post-stimulus onset. Figure 1 illustrates some ERP components.

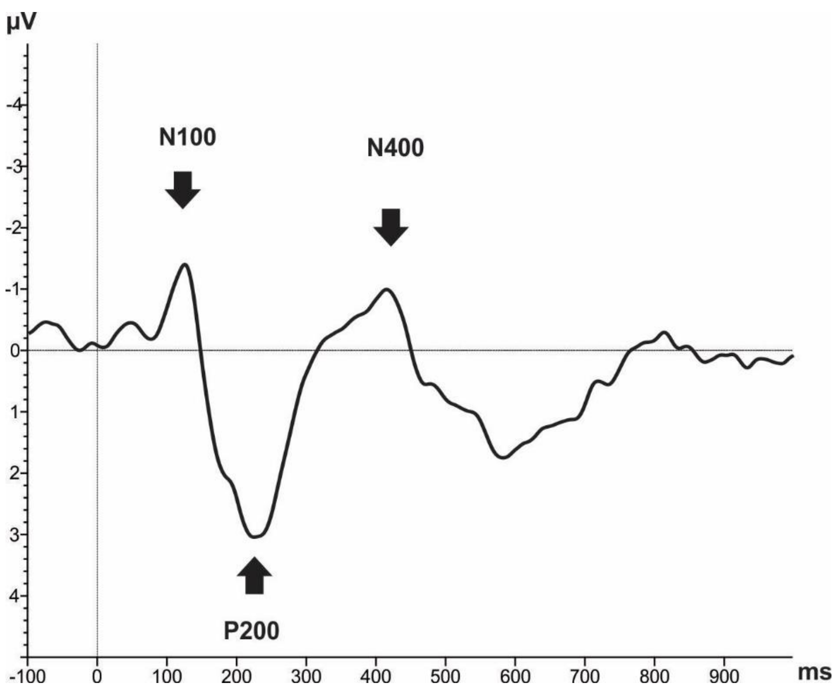

***Figure 1*. Illustration of ERP components.** The N100 component peaks at approximately 100 ms post-stimulus onset. Another peak at approximately 200 ms post-stimulus onset is seen, followed by the N400 component; a deflection peaking at approximately 400 ms post-stimulus onset. Negative is plotted upwards.

ERPs allow us to discriminate the different stages of language processing. A review of ERP components associated with reading follows.

1.6.1 N150. The N150 (also called N170) is an ERP component associated with differentiating orthographic stimuli from other stimuli such as symbols. More specifically, when participants see a stimulus on a screen, a large left-lateralized negativity peaking at 170 ms post-stimulus onset is detected for orthographic stimuli including words and pseudowords when compared to strings of digits or forms (Bentin, Mouchetant-Rostaing, Giard, Echallier, & Pernier, 1999; Maurer, Brandeis, & McCandliss, 2005). In addition, this component has also been shown to be sensitive to letter transposition. In a study by Duñabeitia, Dimitropoulou, Grainger, Hernandez and Carreiras (2012), participants were presented with a stimulus immediately followed by another stimulus that was identical or not to the first one. Three types of stimuli were presented: letters (e.g., DFRD - DFRD), digits (e.g., 39485 - 39845) or symbol strings (e.g., #$%& - #$%&). They were asked to decide whether the second string was the same or different to the first string previously presented. The second string was either the same, or had characters transposed or replaced. Behaviourally, participants responded significantly more slowly and less accurately when identifying transposed letters than transposed digits or symbols. Electrophysiologically, an ERP effect between 100 and 200 ms post-target onset was seen for transposed letters but not for transposed digits or symbols (Duñabeitia et al., 2012). These results indicate that positional information for letters is processed differently than positional information for numbers or symbols, and that there might be perceptual mechanisms in place that are exclusively related to the processing of orthographic information.

Another similar early ERP effect is indexed by the N/P150. This bipolar component has a negative deflection at posterior occipital sites and a positive deflection at anterior sites. This component has been mainly studied during masked priming paradigms. A priming task involves presentation of pairs of stimuli: the prime and the target. The prime is presented first, then during target presentation, participants are typically asked to make a response (e.g., answer whether the target is a word or not). A priming effect occurs when the response to the target is influenced by the prime stimulus (e.g., faster recognition of the word "cat" if it is preceded by the word "dog" than by the word "table"). During masked priming, participants do not consciously detect the prime because its visibility is diminished by the mask (e.g., ##### presented before and/or after the prime), and the prime is presented for a very short time, typically around 30 milliseconds. Masked priming allows the study of automatic processes of word recognition. In a study investigating prime-target name and case consistency, participants were presented with consistent (e.g., o-O) or inconsistent (a-A) lower-uppercase letters. Effects of case consistency were detected very early, beginning at around 100 ms post-stimulus onset and peaking at 150 ms, with inconsistent pairs eliciting a larger P150 at right occipital sites and larger N150 at right anterior sites than consistent pairs (Petit, Midgley, Holcomb, & Grainger, 2006). Similarly, another study has shown that the N/P150 is sensitive to font variation (Chauncey, Holcomb, & Grainger, 2008). During a masked priming paradigm, participants were presented with prime-target stimuli that consisted of either the same or a different word. In addition, prime-target pairs could also vary in size (e.g., table-table) or font (e.g., table-*table*). Chauncey and colleagues found an N/P150 effect for font variation but not for size variation, suggesting that size invariance is achieved earlier than font invariance.

In another masked priming study, Dufau, Grainger and Holcomb (2008) found that the N/P150 component was also sensitive to location. In their paradigm, prime-targets were either centrally aligned on the screen (e.g. table-table) or the prime was shifted by one letter to the left or right of the screen (e.g., _table-table). Their results revealed that repetition priming was only apparent when the prime and target were aligned. The N/P150 was absent when prime words were slightly shifted to the left or right and thus misaligned with the target.

To summarize, both the N150 and N/P150 seem to index brain processes that are specialized in the early perceptual processing of letters, suggesting that letter perception is qualitatively different from perception of other symbols. Moreover, these ERP components not only differentiate processing of letters when compared to other symbols, but also allow researchers to establish that mapping of early visual feature information is sensitive to changes in font type, letter shape, and string location.

1.6.2 N250. Another component is the N250, which is associated with early lexical processing of information. In a masked priming study, Carreiras, Duñabeitia and Molinaro (2009) found that consonants and vowels are processed differently. More specifically, when participants were primed with the vowels of a word (e.g., aue-amuse), the N250 was larger than when they were primed with the full word (e.g., amuse-amuse) whereas there was no difference when processing words that were either primed by its consonants (e.g., pwr-power) or by the word itself (e.g., power-power). Because being primed with the string “pwr” or with the word “power” yields similar ERPs when recognizing “power”, their findings suggests that consonants are the driving force for lexical information during word recognition.

The N250 is also sensitive to the orthographic transposed-letter similarity effect during priming. The N250 has been shown to decrease in amplitude in transposed nonword-word pairs such as “barin-brain” than for substitution nonword-word pairs such as “boain-brain” (Duñabeitia, Molinaro, Laka, Estevez, & Carreiras, 2009; Grainger, Kiyonaga, & Holcomb, 2006). However, no N250 difference is seen in word-word pairs with transposed letters such as “causal-casual” (Duñabeitia, Molinaro, et al., 2009). These results are interpreted within the repetition priming framework whereby in pairs such as “table-table”, the target is recognized faster because it was presented as the prime. Thus, in nonword-word pairs such as “barin-brain” the nonword “barin” facilitates access to “brain” because of its perceptual similarity, thus producing an ERP repetition effect. In word-word pairs such as “causal-casual”, however, such effect is not seen because each word has its own lexical representation. Thus, the N250 seems to be not only sensitive to early lexical processing, but also to semantic properties of the prime.

The N250 is also sensitive to phonological properties. Phonological prime-target pairs such as “trane-train” elicit a similar repetition effect to that observed in orthographic transposed letter priming. However, this effect occurs about 50 ms later than orthographic priming (Grainger et al., 2006). In summary, this component is associated with early orthographic and phonological processing, although evidence also suggests that it is sensitive to semantic information during masked priming paradigms.

1.6.3 P325. This component is associated with processing whole-word representations. The P325 shows larger amplitudes for words than for pseudowords during lexical decision and semantic categorization tasks (Braun et al., 2006; Vergara-Martinez, Perea, Gomez, & Swaab, 2013). During masked priming, the P325 has been shown to be sensitive to repetition effects but only when the prime and target are identical; no effect is observed when the prime and target partially overlap (e.g., “teble-table”) or when the prime and target are unrelated (e.g., “horse-table”) (Holcomb & Grainger, 2006). In addition, the P325 has been shown to be modality general, as an effect can also be observed in both cross-modal and unimodal word priming. In cross-modal priming, the prime is spoken and the target is written whereas in the unimodal priming, both prime and target are presented in the same sensory modality. A study by Friedrich, Kotz, Friederici and Gunter (2004), showed that the P325 was smaller in amplitude for targets in congruent prime-target pairs (“la-lamp”) than from targets in incongruent prime-target pairs (“la-house”) both in cross-modal and unimodal priming. This is in disagreement with Holcomb & Grainger’s repetition effect, as a larger P325 should have been observed for congruent pairs. The discrepancy may be explained by the use of different priming paradigms. Holcomb & Grainger used masked priming with words and pseudowords whereas Friedrich et al. used fragment priming paradigms where the primes were segments of the target words (i.e., prime “la” for the target “lamp”). To summarize, the P325 is associated with whole word representations, as it can differentiate between words and pseudowords. However, other research suggests that it is sensitive to partial word information (as in fragment word priming) in the spoken and visual modalities.

1.6.4 N400. The N400 was discovered by Kutas and Hillyard (1980) in a seminal study investigating the role of context during sentence comprehension. In their study, participants were presented with three types of sentences that ended with words that were: 1) highly congruent: “I take coffee with cream and SUGAR”, 2) improbable but congruent: “I take coffee with cream and CHOCOLATE”, and 3) incongruent: “I take coffee with cream and DOG”. Their findings revealed an unexpected negativity peaking at approximately 400 ms post-stimulus onset that was larger for incongruent than congruent sentences. They named it the N400, a component that since its discovery has been used to investigate a wide range of research questions in the field of cognitive neuroscience.

Kutas & Hillyard (1984) later showed that the N400 congruency effect is inversely related to word expectancy at the end of the sentence (also termed cloze probability: the proportion of participants that give a particular ending word to a sentence), thus suggesting that the effect is associated with the extent to which a word is semantically primed. Indeed, later studies have shown that a similar graded effect is also seen in priming paradigms where the target item is strongly semantically associated (e.g., "cat-dog"), weakly associated (e.g., "cat-paw") or unassociated with the prime (e.g., "cat-chair") (Bentin, McCarthy, & Wood, 1985; Holcomb, 1993; López Zunini, Muller-Gass, & Campbell, 2014). In addition, the N400 is also sensitive to word categories. A graded effect can be observed when a category label cue (e.g., "type of fruit") is followed by incongruent (e.g., "table"), high typicality (e.g., "apple") or low typicality words (e.g., "kiwi"). The graded effect reflects greater ease of access for high than low typicality words, with reduced amplitudes for high typicality words relative to low typicality words, and incongruent exemplars eliciting the largest amplitudes, as expected (Heinze, Muente, & Kutas, 1998; Polich, 1985; Stuss, Picton, & Cerri, 1988).

Furthermore, the N400 congruency effect has been shown with a variety of stimulus types including pictures (e.g., a paper ball versus soccer ball in a soccer game) (Ganis & Kutas, 2003), videos (e.g., stirring with a spoon vs. stirring with a comb in a clip of person cooking) (Sitnikova, Holcomb, Kiyonaga, & Kuperberg, 2008), gestures (e.g., a gesture that mismatch an action in spoken sentence) (Kelly, Kravitz, & Hopkins, 2004), and mathematical operations (e.g., 6X2=12 vs. 6X2=25) (Niedeggen & Roesler, 1999). Thus, the N400 is a component that is associated with language processing, but its effects on a broad range of stimuli highlight its importance in shedding light about when and how linguistic and non-linguistic meaning is processed.

. During visual word recognition, lexical variables also modulate the N400. The amplitude of the N400 is affected by variables that are related to the ease of lexical-semantic processing (Kutas & Federmeier, 2000). For example, the ubiquitous word frequency effect observed during behavioural performance also has its counterpart in the N400: high frequency words elicit smaller N400 amplitudes relative to low frequency words during lexical decision (e.g., Rugg, 1990). A similar effect is observed when words are repeated within an experiment (Rugg, 1985; Rugg, Furda, & Lorist, 1988), suggesting that the smaller N400 amplitudes associated with highly frequent words reflect ease of processing due to repeated encountering of these words over a range of different contexts.

As previously mentioned, words with high orthographic neighbourhood density (OND) are recognized faster than words with low OND during lexical decision, while pseudowords have the opposite effect: high OND pseudowords are classified as non-words more slowly than low OND pseudowords (Andrews, 1989; Carreiras et al., 1997; Coltheart et al., 1977). The N400, however, shows the same pattern of effect for both the word facilitatory effects and pseudowords inhibitory effects. Studies have shown that high OND words and pseudowords elicit larger N400 amplitudes than low OND words during lexical decision, semantic categorization and tasks where experimental items do not require a response (Holcomb, Grainger, & O'Rourke, 2002; Laszlo & Federmeier, 2012; Muller, Duñabeitia, & Carreiras, 2010). In contrast, Taler and Phillips (2007) found smaller N400 for high than low OND words. However, the discrepancy with the above studies may be due to the type of language task. Taler and Phillips investigated OND effects in a sentence congruency paradigm. Thus, it seems OND effects can be constrained by sentence context. A possible explanation for the observed effects in single visual word recognition studies is that orthographic neighbours of the target items become active in parallel due to orthographic overlap, which results in higher level of neural activity. Alternatively, the effects in the sentence congruency paradigm could be due to reduced inhibition –hence reduced N400– required for high than low OND words when they are constrained by sentence context.

Finally, the N400 is not modulated by factors that do not directly affect meaning such as grammatical errors (e.g., "The boy *help* the woman") (Kutas & Hillyard, 1983; Osterhout & Mobley, 1995), thematic role violations (e.g., "For dinner the *toast* would only eat chicken") (Kuperberg, Sitnikova, Caplan, & Holcomb, 2003) or the truth value of a sentence (e.g., "A pigeon is *not* a bird") (Fischler, Bloom, Childers, Roucos, & Perry, 1983).

1.7 Semantic Richness and the N400

The N400 has been the main ERP component investigated in semantic richness studies. One of the first dimensions investigated was imageability. Although imageability and concreteness are two different variables, they are highly correlated (r=.83) (Paivio et al., 1968) and thus, ERP studies often used the terminology interchangeably (e.g., Swaab, Baynes, & Knight, 2002). Therefore, both concreteness and imageability studies will be discussed here. Moreover, behavioural semantic richness studies investigating imageability have typically looked at behavioural advantages in paradigms where concrete words were the items under investigation, and abstract words were considered fillers and thus, were not included in the analyses (e.g., Pexman et al., 2008; Yap et al., 2011). By contrast, most of the ERP studies discussed here (with the exception of Swaab et al.) looked at the ERP correlates of concrete vs. abstract words. Finally, many of these studies investigated the effect within sentence context or in semantic priming paradigms as opposed to single visual word recognition (which is the focus of this thesis). These ERP studies, however, provide valuable evidence for how imageability/concreteness are processed, and how they interact with task demands and context.

Kounios and Holcomb (1994) investigated concreteness effects during both a lexical decision task and a concrete/abstract semantic categorization task. Their results revealed larger N400s for concrete than abstract words in both types of task, with the effect being larger in the semantic categorization task. In addition, a similar N400 effect has been found in a sentence congruency task using a similar paradigm as in Kutas and Hillyard's classic study. Recall that Kutas and Hillyard found a larger N400 for sentences ending with incongruent words relative to congruent words. In addition to replicating this effect, Holcomb, Kounios, Anderson and West (1999) found a larger N400 effect for incongruent concrete word endings than incongruent abstract word endings, while congruent concrete and abstract word endings did not differ from each other. These results suggest that contextual and semantic richness effects dynamically interact to process meaning. More specifically, these results show that concreteness effects can be minimized with supportive context.

West and Holcomb (2000) investigated concreteness comparing the effects of three different types of sentence verification tasks in which the last word of each sentence was concrete or abstract. In each type of sentence, participants had to make a truthfulness judgement that involved either imagery (e.g., "It is easy to form a mental picture of a lion/attitude"), semantic processing (e.g., "It is unusual for people to have a lion/attitude"), or surface processing (e.g., "The letter *l* appears in the word lion/attitude"). Results revealed N400 concreteness effects in both the imagery and semantic tasks but no effect during the surface task, again highlighting the dynamic interplay between semantic richness and the processing of meaning. Another study investigating concreteness/imageability effects and its dynamics with context found that high imageability words exhibited larger N400 amplitudes than low imageability words in an auditory priming task where targets were either related (e.g. "atom-molecule") or unrelated to the prime word (e.g., "peace-molecule") (Swaab et al., 2002). These results are at odds with those of Holcomb's research group, because in Swaab's study, both high and low imageability words exhibited the same effect regardless of context (i.e., related vs. unrelated). However, the authors suggested the discrepancy may be explained by the type of context. Holcomb et al.'s context consisted of sentences (strong context), whereas in Swaab et al., the context was limited to a single word (i.e., the prime). As previously mentioned, some studies used the terms concreteness and imageability interchangeably (e.g., Swaab et al.; West & Holcomb, 2000) or did not control for imageability ratings (e.g., Kounious & Holcomb, 1994; Holcomb et al. 1999). Although both variables are highly correlated, they are not identical. For example, imageability ratings only explain 72% of the variance in concreteness ratings (Kousta, Vigliocco, Vinson, Andrews, & Del Campo, 2011). In addition, concreteness ratings (e.g., MRC database) have a bimodal distribution whereas imageability ratings have an unimodal distribution (Kousta et al., 2011). Thus, concreteness and imageability findings should be interpreted with caution.

An additional study highlighting the dynamics of concreteness effects found that when a block of concrete words preceded a block of abstract words during a lexical decision task, concrete and abstract words did not differ in the N400 amplitudes they elicited. However, when abstract words preceded concrete words or when both types of words were mixed throughout the task, the classical concreteness N400 effect was replicated (Tolentino & Tokowicz, 2009). The authors concluded that when participants were required to process a block of concrete words followed by a block of abstract words, abstract word processing behaved more like concrete word processing; that is, they were perceived in a more enriched manner than they usually would be, perhaps signifying that when abstract words are presented after processing a number of concrete words, more sensory experience than usual is associated with them, which in turn enrich its perception.

To summarize, the concrete/abstract ERP effect is clearly modulated by task demands. Although the typical effect seems larger N400 amplitudes for concrete or highly imageable words relative to abstract low imageability words, this effect can be modulated by manipulating task instructions and type of sentences (as in West and Holcomb) or by order of word type presentation (as in Tolentino and Tokowicz). However, it is very important to treat concreteness and imageability as separate variables given that they are not identical. Future studies should aim to investigate both variables separately (and not use them interchangeably) to further elucidate its effects.

The majority of semantic ambiguity ERP studies have relied on semantic priming paradigms. As previously mentioned, the focus of this thesis is on single word recognition; however, priming studies investigating lexical ambiguity will be briefly discussed because they shed light on how this semantic richness dimension is represented and processed in the brain.

Behavioural studies have shown that reaction time effects observed during lexical decision differ as function of type of ambiguity (homonymy vs. polysemy) (Rodd et al., 2002). More specifically, homonymous words are recognized more slowly than unambiguous words during lexical decision, while polysemous words are recognized more quickly than words with few senses (Rodd et al., 2002). In agreement with this finding, differential N400 effects of homonymy and polysemy have also been found during semantic priming (Klepousniotou, Pike, Steinhauer, & Gracco, 2012). Participants in Klepousniotou et al. were presented with several prime-target pairs at a short inter-stimulus interval of 50 ms: 1) homonym-related dominant meaning (e.g., “ball-hit”), 2) homonym-related subordinate meaning (e.g., “ball-dance”), 3) homonym-unrelated (e.g., “ball-doctor”), 4) polysemous-related dominant meaning (e.g., “rabbit-hop”), 5) polysemous-related subordinate meaning (e.g., “rabbit-stew”), and 6) polysemous-unrelated (e.g., “rabbit-chair”). Recall that during semantic priming, a smaller N400 is detected for related than for unrelated targets (Bentin et al., 1985). Klepousniotou and colleagues found that in the homonymy condition, dominant and subordinate targets showed reduced N400 amplitudes relative to unrelated targets. However, for the subordinate targets, the effect was limited to the left hemisphere electrode sites. For the polysemy condition, both dominant and subordinate targets exhibited similar reduced N400 amplitudes relative to unrelated targets.

These results demonstrate that types of lexical ambiguity are differentially represented in the brain. The authors suggested that the multiple unrelated meanings of a homonymous word have multiple representations in the brain that compete for activation, while the related senses of a polysemous word have one single representation (because their different meanings are related). Thus, differences in brain activation patterns are observed for the dominant and subordinate meanings of homonymous words, while dominant and subordinate senses of polysemous words do not exhibit differences in the N400 effect.

Using the same priming paradigm as in Klepousniotou et al. (2012), Mac Gregor, Bouwsema and Klepousniotou (2015) investigated the time course of meaning activation in homonymous and polysemous words by using a longer inter-stimulus interval of 750 ms (as opposed to 50 ms in Klepousnioutu et al). Their findings revealed that for targets related to the dominant and subordinate senses of polysemous primes, the reduced N400 effect relative to unrelated targets was still observed. However, for targets related to the dominant and subordinate meanings of homonymous primes, the reduced N400 effect relative to unrelated targets was no longer observed. MarcGregor et al. suggested that the related senses in polysemous words strengthen its core representation in the brain; both senses remain active until context is available, whereas the unrelated meanings in homonymous words compete for activation and thus decay rapidly in the absence of supporting context. Thus, the N400 reduced effect for homonymous words is observed when the target word rapidly follows the homonymous prime (Klepousniotou et al., 2012) but is no longer observed when the target word is presented after a relatively long delay (MacGregor et al., 2015), indicating processing differences in lexical ambiguity resolution for homonymous and polysemous words.

Our research group investigated polysemous words in the context of single visual word recognition (we refer to it as the semantic richness dimension number of related senses). In agreement with priming studies, we observed smaller N400 amplitudes in words with many related senses when compared to words with few related senses in a lexical decision task while controlling for other lexical and semantic variables (Taler, Kousaie, & López Zunini, 2013). We suggested that the smaller N400 amplitude observed for words with high number of senses relative to words with low number of senses was due to reduced processing demands when recognizing words that are associated with multiple *related* senses. Further research should aim to understand the effects of words with unrelated meanings (homonyms) and related senses (polysemous words) during different types of single word recognition tasks.

Studies focusing on the semantic richness dimension number of features (NoF) have reported inconsistent results. Some studies found smaller N400 amplitudes for high NoF than for low NoF words (Amsel & Cree, 2013; Kounios et al., 2009), while others found the opposite effect (Amsel, 2011; Rabovsky, Sommer, & Abdel Rahman, 2012). As previously mentioned, a particular semantic richness dimension can yield different performance results depending on task demands (e.g., Yap et al., 2012); thus, task demands may also influence the direction and magnitude of the N400 effect. Therefore, the inconsistency in NoF results may be explained in part by the nature of the tasks used in these studies. Participants in Kounios et al. (2009) performed a semantic relatedness task, where they had to decide whether word pairs where related or not. Participants in Amsel & Cree's study (2013) performed a concrete/abstract semantic categorization task, while participants in Amsel (2011), silently read words and were asked to judge their imageability after the word was presented. Finally, participants in Rabovsky et al.'s study (2012) performed a lexical decision task. Thus, it appears that discrepancies reported for the neural correlates of NoF could be due to differences in task demands. The semantic relatedness and categorization tasks in Kounios et al. (2009) and Amsel & Cree (2013) may rely more on semantic access than the silent reading and lexical decision tasks in Amsel (2011), and Rabovsky et al. (2012). More reliance on semantic information access in some tasks relative to others may account for distinct patterns of N400 effects.

1.7.1 Semantic richness dimensions investigated in this thesis. This thesis focused on the dimensions of number of associates (NA), number of semantic neighbours (NSN) and body-object interaction (BOI). The NSN and BOI dimensions have been investigated in a number of behavioural studies (Buchanan et al., 2001; Pexman et al., 2008; Siakaluk, Pexman, Aguilera, et al., 2008; Siakaluk, Pexman, Sears, et al., 2008; Yap et al., 2012; Yap et al., 2011), and there is evidence that their effects are modulated by task demands (Pexman et al., 2008; Yap et al., 2012; Yap et al., 2011). However, the electrophysiological dynamics of NSN and BOI have not yet been investigated. The experiments in this thesis are the first to examine their ERP correlates and compare its effects in two different language tasks. In contrast, three ERP studies have investigated the NA dimension during single visual word recognition; they are discussed below.

Similar to the NoF findings, the N400 effects in the NA literature are not consistent. Muller et al. (2010), and Laszlo and Federmeier (2012) found that words with high NA elicited larger N400s than words with low NA. In contrast, Rabovsky et al. (2012) did not observe any difference in high vs. low NA words. This discrepancy may again be explained by variations in task demands. Participants in Rabovksy et al. and Muller et al. performed a lexical decision task, while participants in Laszlo & Federmeier’s study performed a task where target items were free of lexical decision. In this task, participants only had to decide whether filler items were a proper noun or not. Discrepancies may also be accounted for by a number of other factors. Rabovsky et al. controlled for the semantic richness dimension of NoF, while Lazslo and Federmeier did not. NA and NoF are positively correlated (Yap et al., 2011) and it is thus important to control for one semantic richness dimension while investigating the other. In addition, a major caveat in Muller et al.’s experiment was that words with many associates were significantly higher in imageability than words with few associates. As previously discussed, imageability is an important variable to control for, because N400 amplitudes are affected by imageability. Moreover, Muller et al.’s N400 effect was in the same direction as concreteness/imageability studies (e.g., West & Holcomb, 2000). Finally, Laszlo & Federmeier performed regression analyses on single items while the other studies performed standard ERP ANOVA analyses. Thus, there are many possible explanations for the different results found in these studies.

The NA experiment in this thesis aimed to control for the discrepancies among the above studies, by examining only the NA variable while controlling for NoF and imageability measures. In addition, using the same set of stimuli in both tasks while only varying the task instructions could aid to better elucidate NA dynamics.

1.8 Theories of the N400

Theories of the N400 aim to map its effect to cognitive processes. In the integration view, the N400 amplitude is thought to reflect how easily a stimulus can be integrated into a given context (e.g., Holcomb, 1993; Rugg et al., 1988). Depending on the type of task and evidence available, various versions of the integration view exist. For example, within the context of the N400 repetition effect, it has been posited that a reduction of the N400 amplitude for repeated stimuli may be due to re-accessing the representation in semantic memory. When a stimulus is presented for the first time, processes associated with the integration of the stimulus characteristics (e.g., its meaning) are set in action and are reflected in the N400 amplitude. When the same stimulus is presented again, processes occur with less effort because less integration is necessary due to the recent activation, thus resulting in smaller N400 amplitudes relative to the first presentation of the stimuli (Rugg, 1990; Rugg et al., 1988). Within the context of semantic priming (i.e., in tasks consisting of word pairs that are related or unrelated), Holcomb (1993) suggested that the integrative process is activated in a top-down manner, whereby information available in semantic memory from the prime word can benefit and facilitate the processing of the target word.

At the sentence or discourse level, the integration process is explained by semantic unification, which "refers to the integration of word meaning into an unfolding representation of the preceding context" (Hagoort, Baggio, & Willems, 2009). According to this view, a coherent interpretation of a sentence is constructed by integrating several sources of information that can include world knowledge, information about the speaker, or discourse information. For example, Hagoort, Hald, Bastiaansen and Petersson (2004) found very similar N400 effects for incongruent sentences endings (e.g., "Polar bears are sugar") and for sentences that violated world knowledge (e.g., "Polar bears are red"). Another study found larger N400 amplitudes for sentences that were incongruent with information about the identity of the speaker (e.g., a male voice saying: "If I only looked like Julia Roberts") relative to congruent exemplars (Van Berkum, van den Brink, Tesink, Kos, & Hagoort, 2008).

One difficulty with the integration view is that one would expect larger N400 amplitudes for false sentences such as "An apple is not a fruit". However, it has been shown that the N400 is not sensitive to the truth value of a sentence (e.g., Fischler et al., 1983). In addition, the integration view assumes that conscious attention is necessary for integration to take place. However, N400 effects of semantic congruity have been observed during sleep (Brualla, Romero, Serrano, & Valdizán, 1998; Ibáñez, López, & Cornejo, 2006) and during unconscious priming (Rolke, Heil, Streb, & Hennighausen, 2001).

The inhibition hypothesis offers a different explanation for the functionality of the N400. This hypothesis postulates that the N400 amplitude is modulated by the incompatible information that needs to be inhibited (Debruille, 2007). To test this hypothesis Debruille (1998) parted from the premise that real words activate words that resemble them, thus activating knowledge that may be incompatible with the context where it is presented. In his study, participants performed a LDT and were presented with two types of low frequency words: 1) look-alike words, that is words that had a high frequency word as orthographic neighbour (e.g., “bribe” is a low frequency word that has the high frequency word “bride” as orthographic neighbour), 2) eccentric words, that is words that did not have orthographic neighbours of high frequency nor resembled a high frequency word (e.g., “circus”). Debruille’s results revealed that look-alike words exhibited larger N400 amplitudes than eccentric words, consistent with the idea that more inhibition is required for look-alike words. One caveat of this study is that while look-alike words had an orthographic neighbourhood density (OND) of 3.9, eccentric words had an OND of 1.5. Thus, it is possible that the N400 difference observed may have been due to OND.

In another study that used semantic priming, participants were presented with word triples that included a distractor word, a prime and a target. The distractor appeared first, followed by the prime and then the target stimulus. In one condition, participants were asked to ignore the distractor, while in the other, they were asked to attend to the distractor (Debruille et al., 2008). In agreement with the inhibition hypothesis, N400 amplitudes were larger for distractor words in the ignore condition than in the attend condition, thus reflecting the idea that stronger inhibition of the knowledge associated with the distractor words is required in the ignore relative to the attention condition.

One challenge with the inhibition hypothesis is that it remains undertested. The N400 effects observed in a wide range of situations suggest that this component is a part of a complex cognitive process that involves semantic memory and access to meaning, thus it may index both integration and inhibition depending on the task at hand. An attempt to merge both views, supported by empirical evidence, would have the potential to advance our understanding of the N400 functionality.

In contrast to the above views, other theories aim to link neural functions with the N400 effect. Federmeier and Laszlo (2009) posited that the N400 is a reflection of the binding process. Neural binding refers to the integration of diverse neural information in order to form a cohesive experience. This hypothesis postulates that neural activity can be combined in different synchronization patterns that allow us to perceive stimuli in a context-dependent manner (see Senkowski, Schneider, Foxe, & Engel, 2008, for a review). The N400 arises from the temporal synchrony of a broad neural network. Federmeier and Laszlo state that this synchrony creates a multimodal representation using information available in long-term memory. Thus, according to this view, concepts and their meanings are dynamically shaped and context-dependent. That is, in the case of word recognition, a concept will be formed by the binding of neural activity associated with pieces of information such as semantic memory, task demands, and perceptual and lexical-semantic characteristics of a word.

1.9 Models of Visual Word Recognition

Computational models of word recognition are key to unraveling the complexity of language processes. They can make predictions about how humans access word meaning and have the potential to offer a mechanistic account of normal word recognition processes as well as how processes can be affected by disorders such as dyslexia, aphasia or Alzheimer's disease. Predictions provided by computational models can in turn generate new hypotheses that can be empirically tested. Given their importance, they are discussed in this section.

1.9.1 Earlier models. One of the first models of word recognition is Morton's logogen model (Morton, 1969, 1980). According to this model, logogens –from the Greek words "logos" (words) and "genus" (birth) – contain information about the properties of a word such as its orthography, its sound, and its meaning. Each logogen has an activation threshold. When incoming information about a particular word property reaches a threshold, the logogen gets activated and the word is recognized. For example, the logogen associated with word frequency varies in high and low frequency words such that high frequency words have lower activation threshold than low frequency words. Consequently, high frequency words are recognized more quickly than low frequency words.

By contrast, Forster's autonomous serial search model (Forster, 1976) explains word recognition as a matching process between incoming information and the stored knowledge of a word (the process is analogous to looking for a book in a library). The information is organized into "access files" classified as orthographic, phonological or semantic in nature. When a word is presented, the constructed perceptual representation is located in one of the access files. When the word is located in the access file, it is then compared to a master file that contains its complete lexical information and the word is recognized. Each access file is organized according to frequency, with most frequent words at the top of the file, thus explaining the facilitatory effects for high frequency words.

In Becker's verification model (Becker, 1979), there are two processes involved in word recognition: sensory-feature extraction and verification. During sensory-feature extraction, possible words in visual memory that are consistent with the sensory features of the perceived word are activated. Then, during verification, a word is selected from the possible set of words in visual memory and compared to the perceived word. If a match is found, the word is recognized. If there is no match, the next word in visual memory is compared to the perceived stimulus and so on until a match is found. In this model, the facilitatory word frequency effect is explained by high frequency words being considered for verification before lower frequency words.

These earlier models were of the “box and arrow” type, and did not specify what went on in the boxes. In addition, they assumed that semantic information would only activate after a word was recognized. With the advent of computational models of word recognition in the 1980s, clear specifications of what was going on in the boxes could predict and simulate real data. A discussion of the most influential computational models follows.

1.9.2 Connectionist models. Connectionist models are inspired by the architecture of neural networks. These models describe word recognition with a series of interconnected processing units (the network) where activation in one unit spreads to other units connected to it (spreading activation). Another central aspect is that the units are altered through learning algorithms (e.g., Hebbian learning), thus bringing the output closer to empirical data (simulation).

The Interactive Activation model (IA) first proposed by McClelland and Rumelhart (1981) had three basic assumptions: 1) perceptual processing occurs at different levels and is handled by different systems, 2) perception at different levels occurs in parallel, 3) perception is interactive. The original model included three levels, features, letters and words, each represented by nodes (localist representation). For example, there is a node for each word, and a node for each letter within a string of letters. Furthermore, they proposed that processes at each level can occur simultaneously. More specifically, processing at the feature level, letter level and word level are processed in parallel. Finally, they proposed that bottom-up and top-down processes jointly determined word recognition in a feedforward/feedback manner. In other words, information about letters or words nodes could feedback information to the lower feature level, while feature level nodes could feedforward information to higher level nodes. Later, Balota (1990) proposed adding a semantic level to the IA model. Within this framework, the facilitatory effects of semantic richness are accounted for by top-down feedback of semantically rich words to the orthographic level system.

Later, a Parallel Distributed Processing (PDP) model that applied most of the assumptions in the IA was developed (Seidenberg & McClelland, 1989). However, instead of words and their properties being locally represented by separate systems, they were characterized as a distributed pattern of activity of neuron-like units. The classic PDP model is represented by a network of orthographic, phonological and semantic processing units where each word is represented as a different pattern of activity comprised of the three levels of processing. Thus, word recognition relies on a common cognitive system where orthography, phonology and semantics interpedently interact. Activation flows from orthographic and phonologic to semantic representations through weighted connections in a bidirectional (feedforward/feedback) manner, and it eventually settles into a distributed pattern that represents the word or concept (Seidenberg & McClelland, 1989). Because of their rich representations, semantically rich words are thought to activate more units in the semantic layer and thus provide greater feedback activation to the orthographic layer than more semantically impoverished words, explaining the facilitatory effects of semantically rich words during word recognition (Hino et al., 2002).

1.9.3 Biologically-plausible models. One recent advance in computational models of word recognition is the incorporation of electrophysiological simulations within the framework of connectionist models. This is achieved by incorporating into the architecture of the model other properties of neural networks, such as simulation of excitatory and inhibitory neurons and the existence of fewer inhibitory than excitatory neurons.

Following the principles of the parallel distributed processing model (PDP), Laszlo and Plaut (2012) successfully simulated N400 ERP dynamics during recognition of words, pseudowords, acronyms and illegal strings. Both the N400 in the model and the N400 observed in the empirical data exhibited an effect of orthographic neighbourhood density regardless of lexicality. In addition, their regression analyses revealed that the slopes representing the relationship between orthographic neighbourhood density and lexicality were very similar in the model and the empirical data.

More recently, Laszlo and Armstrong (2014) simulated the N400 repetition effect. A repetition effect is characterized by a reduction in N400 amplitudes when a stimulus is presented a second time. An explanation that is well accepted in the field of cognitive science is that when the stimulus is repeated, less lexical processing is required during the second presentation because the stimulus has been recently activated (Rugg, 1985). Thus, the second presentation is processed with less effort. Laszlo and Armstrong offered a mechanistic account of the N400 repetition effect by incorporation the dynamics of post-synaptic potentials into their computational model (recall that ERPs reflect the summed activity of post-synaptic potentials). A post-synaptic potential property is that neurons stop firing with repeated stimulation (that is, they become fatigued). Using a mathematical function that simulated post-synaptic fatigue, Laszlo and Armstrong successfully simulated the N400 repetition effect, offering a mechanistic account for the process.

The brain is probably the most intricately complex organ in our bodies, as such, it is exceptionally difficult to model. However, computational models that attempt to incorporate neuronal properties have great potential for exploring the brain mechanisms of access to word meaning. Future studies should aim to incorporate semantic richness effects associated with the N400 into a computational model to fully understand the process.

1.10 Thesis Aims and Hypotheses

Few studies have systematically investigated the temporal brain dynamics of semantic richness and task demands. Thus, this thesis aimed to fill this gap in the literature by systematically comparing the ERP correlates associated with a given semantic richness dimension (NA, NSN, and BOI) in two different types of language tasks (LDT vs. SCT).

The two main goals of this thesis are: 1) to identify the influence that a particular semantic richness dimension exerts on performance of two different language tasks. In other words, is there an interaction between a semantic richness dimension and task demands?, 2) to identify the N400 profile associated with each semantic richness dimension and task demands. More specifically, when investigating a particular semantic richness dimension, do ERPs differ (in terms of magnitude and direction) between the LDT and SCT?

The hypotheses in this thesis are as follows:

1. Words with high NA, NSN or BOI will elicit faster reaction times than words with low NA, NSN or BOI, respectively, in both the LDT and the SCT.
2. The reaction time effect elicited by high NA, NSN or BOI words will be greater in the SCT than in the LDT.
3. The N400 will be smaller for high NA, NSN or BOI words than for low NA, NSN or BOI words, respectively, in both the LDT and the SCT.
4. The N400 effect will be larger in the SCT than in the LDT.

Chapter 2: Number of Associates

2.1 Background and Hypotheses

The dimension number of associates (NA) has been investigated both in behavioural and neurophysiological studies. Several studies have shown that words with many associates are recognized faster than words with few associates in lexical decision and semantic categorization tasks (Balota et al., 2004; Buchanan et al., 2001; Duñabeitia et al., 2008; Locker et al., 2003; Pexman et al., 2007; Yates et al., 2003). Although the effects may disappear when other dimensions are accounted for (Yap et al., 2011).

ERP studies have reported inconsistent results with some studies finding larger N400 amplitudes for high than low NA words (Muller et al., 2010; Laszlo & Federmeier 2012), while others did not observe an effect (Rabovsky et al., 2012). The lack of agreement in these studies may be due to a number of factors such as variations in task demands or lack of control of other semantic richness dimensions (discussed in detail in the introduction sub-section 1.7.1).

The NA experiment in this thesis aimed to control for the discrepancies among the above studies, by examining only the NA variable while controlling for other semantic richness measures. In addition, using the same set of stimuli in both tasks while only varying the task instructions aided to better elucidate NA dynamics. In this experiment, participants performed either an LDT or a living/non-living SCT. Comparisons of the two tasks can help to isolate context-dependent NA effects because the two paradigms are identical in terms of stimulus presentation and motor response and only differ in the type of decision to be made.

I hypothesized that reaction time would be faster and N400 amplitudes would be smaller for high NA than for low NA words in both tasks. However, due to the dynamic nature of semantic richness effects, I hypothesized that both behavioural and electrophysiological effects would be larger in the SCT than in the LDT.

2.2 Methods

2.2.1 Participants. Participants were 48 (34 females) right handed English monolingual young adults recruited through printed ads from the University of Ottawa and through social media ads from the community. Their mean age was 21.14 (+/-2.73) and they had 15.31 (+/-1.61) years of education at the time of testing. Participants were randomly assigned to one of two groups (n=24 per group): one group performed a LDT and the other performed a SCT. Across groups, participants did not differ significantly in age or education ($p > .1$ in both cases). All participants completed a self-report health and history questionnaire to confirm they were in good health, had no neurological or psychiatric history, and were not taking any medication known to affect cognitive function. Participants signed a consent form approved by the ethics committee at Bruyère Research Institute and the University of Ottawa. They were compensated $10 an hour for their participation.

2.2.2 Testing procedure. Participants were seated in a chair at about 60 cm from a computer monitor while their EEG was being recorded. Depending on the group to which they were assigned, they were asked to perform a lexical decision task or a living/non-living semantic categorization task. Testing took approximately 1.5 hours including set-up of the EEG cap.

2.2.3 Experimental tasks. The tasks were programmed and presented with E-prime 2.0 software (Psychology Software Tools, Pittsburgh, PA, USA). They were presented on a Dell

OptiPlex 780 desktop computer with Windows XP Professional operating system, an Intel Core 2 Duo processor and a 20’’ screen.

2.2.3.1 Lexical decision task. In the LDT, a fixation cross (+) was presented for a randomly varied inter-stimulus interval between 800 and 1500 ms at the center of the screen. Next a stimulus (either a word or a pseudoword) was presented in white 18-point Courier New font on a black background for 2000 ms or until the participant made a response. Participants were instructed to indicate whether each stimulus was a word or not as quickly and as accurately as possible by pressing one of two keys on the keyboard. Response buttons were counterbalanced such that half of the participants responded by pressing the “A” to indicate a word or the “L” to indicated a pseudoword while the other half of the participants did the opposite.

2.2.3.2 Semantic categorization task. In the SCT, a fixation cross (+) was presented for a randomly varied inter-stimulus interval between 800 and 1500 ms at the center of the screen, next a stimulus (note that the word stimuli are the same set used in the LDT but participants made a living or non-living decision) was presented in white 18 point Courier New font on a black background for 2000 ms or until the participant made a response. Again, participants were instructed to respond whether each stimulus was a living or a non-living entity by pressing one of two buttons. Response buttons “A” and “L” where counterbalanced among participants in the same way as in the LDT.

2.2.4 Stimuli. The stimuli in the LDT and SCT were identical, thus allowing for a systematic comparison of semantic richness effects across the two tasks. Each task (LDT or SCT) consisted of a total of 60 words high in NA and 60 words low in NA. The stimuli were balanced across a number of variables known to influence behavioural performance and N400 amplitude.

The variables controlled for included word length, word frequency (Hyperspace Analogue to Language or HAL frequency), orthographic neighbourhood density and bigram frequency by position (the English Lexicon Project) (Balota et al., 2007), concreteness, familiarity, and imageability (MRC Psycholinguistic Database) (Coltheart, 1981). NA was determined using the University of South Florida Free Association Norms (Nelson et al., 1998).

The following semantic richness dimensions were also controlled for where data were available: number of semantic features (McRae et al., 2005), as well as the two other dimensions investigated in this thesis (NSN and BOI) (Bennett et al., 2011; Durda & Buchanan, 2006; Tillotson et al., 2008).

In the LDT, an additional 120 pseudowords were generated using the English Lexicon Project (Balota et al., 2007) and were matched to the words in length, orthographic neighbourhood density and bigram frequency by position. Information on lexical and semantic variables for the stimuli is provided in table 1.

Because the words were identical for the LDT and SCT, 60 of the words were living entities while the other 60 were non-living entities. Living and non-living stimuli were further balanced across all the variables and dimensions mentioned above. Information on lexical and semantic variables by living/non-living stimuli is provided in table 2.

Table 1

NA Stimuli Characteristics

Variables	**NA**		**p-value**	**Pseudoword (SD)**	**p-value (NA vs. Pseudoword)**
	High(SD)	**Low(SD)**			
Number of Associates	18.18(15.61)	3.37(1.30)	<.001		
Word Length	4.85(1.45)	5.28(1.71)	.14	5.12(1.57)	.78
Frequency (log HAL)	8.41(1.11)	8.20(1.18)	.30		
Orthographic Neighbourhood Density	8.14(6.95)	6.48(7.21)	.20	7.10(6.49)	.81
Bigram Frequency	2416.80(1294.00)	2682.97(1420.00)	.30	2416.40(971.10)	.40
Concreteness	584.52(43.11)[a]	582.35(39.41)[b]	.80		
Familiarity	510.31(51.68)[c]	508.72(40.62)[b]	.87		
Imageability	579.39(48.74)[c]	574.00(48.40)[b]	.60		
Number of Features	14.34(4.34)[d]	12.78(4.44)[e]	.22		
Number of Semantic Neighbours	2.23(2.16)	2.72(5.06)	.50		
Body-Object Interaction	4.86(0.83)[f]	4.56(1.00)[g]	.20		

a=available for 48 items, b=available for 43 items, c=available for 49 items, d=available for 22 items, e=available for 27 items, f=available for 40 items, g=available for 25 items.

Table 2

NA Living-Non Living Items Characteristics

Variables	**Living**	**Non-Living**	**p-value**
Number of Associates	12.50(17.64)	9.05(6.30)	.16
Word Length	4.85(1.45)	5.28(1.71)	.14
Frequency (log HAL)	8.16(1.04)	8.44(1.24)	.20
Orthographic Neighbourhood Density	7.98(8.20)	6.63(5.80)	.30
Bigram Frequency	2424.60(1222.45)	2675.17(1473.86)	.31
Concreteness	591.24(37.96)[a]	576.86(43.05)[b]	.10
Familiarity	506.49(44.58)[c]	512.27(48.60)[b]	.60
Imageability	585.74(46.10)[c]	569.06(48.60)[b]	.10
Number of Features	14.20(4.91)[d]	12.60(3.67)[e]	.21
Number of Semantic Neighbours	2.08(2.00)	2.87(5.12)	.16
Body-Object Interaction	4.56(0.86)[f]	4.87(0.93)[g]	.18

a=available for 42 items, b=available for 49 items, c=available for 43 items, d=available for 27 items, e=available for 22 items, f=available for 26 items, g=available for 39 items.

2.2.5 EEG recording. The continuous EEG was recorded using a commercially available nylon cap with 32 tin electrodes (Electro-Cap International Inc., Eaton, OH, USA) placed according to the international 10-20 system of electrode placement. A cephalic site was used as ground and linked ears were used as the reference. Four additional electrodes were placed on the face to record horizontal and vertical eye movements. The horizontal electro-oculogram was recorded from electrodes placed at the outer canthus of each eye and the vertical electro-oculogram from electrodes placed above and below the left eye. The EEG was amplified with NeuroScan NuAmps (NeuroScan, El Paso, TX, USA), sampling rate was 500 Hz in a DC to 100 Hz bandwith, and impedances were kept below 5 Ω.

EEG data was processed offline using Brain Vision Analyzer 2.1 (Brain Products, GmbH, Munich, Germany). A low pass 20 Hz filter was applied and Independent Component Analysis (Makeig, Bell, Jung, & Sejnowski, 1996) was used to identify eye movements and blinks that were statistically independent of the EEG activity. Next, the continuous EEG was segmented into discrete 1100 ms epochs starting 100 ms before the onset of the stimulus. The 100 pre-stimulus period served as a zero voltage baseline period and epochs were baseline corrected. Any epochs containing EEG activity exceeding ±100 µV on the electrodes of interest were rejected from averaging.

Epochs were sorted and averaged based on stimulus condition of the experimental task (high NA and low NA). Only correct responses were included in the averages and all averages contained a minimum of 30 trials.

2.2.6 Statistical analyses. All data was analyzed with the Statistical Package for the Social Sciences v. 20 (SPSS), (IBM, Armonk, NY, USA).

2.2.6.1 Behavioural performance. Trials with reaction times (RT) exceeding ±2.5 standard deviations from the mean were excluded as outliers. Accuracy and RT were analyzed in two separate 2X2 Mixed ANOVAs with the within-subject factor NA (high, low) and between-subject factor Task (LDT and SCT).

In addition, independent sample t-tests item analyses for both accuracy and RT were performed for each task with high vs. low NA as the independent variable.

2.2.6.2 ERP data. Electrode sites were grouped into 3 regions of interest (ROIs) that included 5 electrodes each: left lateral (F3, FC3, C3, CP3, P3), midline (Fz, FCz, Cz, CPz, Pz), and right lateral (F4, FC4, C4, CP4, P4). Mean amplitudes from 350 to 550 ms post-stimulus onset were chosen for analyses. A mixed ANOVA was conducted with the following within-subject factors: NA (2 levels), Electrode (5 levels), ROI (3 levels) and the between-subject factor Task (LDT vs. SCT)[1]. Interactions involving the factor Task were decomposed with repeated measures ANOVAs on each Task with the factors NA, Electrode and ROI. When interactions were significant within a task, additional post-hoc tests with Fisher's Least Significance Difference (LSD) pairwise comparisons were carried. A Greenhouse-Geisser correction procedure was used for all ERP analyses when sphericity was violated (Geisser & Greenhouse, 1958), and the uncorrected degrees of freedom are reported, as per convention.

[1] Analyses were also carried with an additional factor Time (4 levels) consisting of mean amplitudes of the following 50 ms bins: 350-400, 400-450, 450-500 and 500-550. The Time factor, however, did not interact with NA or Task, and thus did not yield additional information. Therefore, only analyses using the whole interval mean amplitude are reported (i.e., without the Time factor).

2.3 Results

Three participants from the LDT and three from the SCT group were excluded from all analyses due to noisy EEG data. Thus, there was a final sample of 21 participants in each group.

2.3.1 Behavioural results. In the LDT, 2.7% trials were excluded as outliers while 2.3% were excluded in the SCT.

ANOVA analyses on accuracy and RT did not reveal a main effect of NA nor any interaction involving this factor ($F<1$ for all tests). Table 3 displays mean accuracy and RTs for each task. However, item analyses revealed different results. Independent sample t-tests performed for each task revealed that high NA words elicited more accurate responses ($t(118)=3.91$, $p<.001$, $d=.71$) and faster reaction times ($t(118)=-2.82$, $p=.006$, $d=.52$) than low NA words during the LDT. Accuracy ($t(118)=.60$, $p=.55$) and RT ($t(118)=-1.1$, $p=.27$) did not significantly differ between high and low NA words during the SCT. Mean accuracy and reaction time are displayed in table 4.

Table 3

Reaction Time (in ms) and Accuracy (%) for NA Subject Analyses

Task	NA	Reaction Time (SD)	Accuracy(SD)
LDT	High	712.93(91.58)	93.73(5.00)
	Low	711.12(101.04)	93.50(5.29)
SCT	High	739.88(86.64)	93.88(3.51)
	Low	753.06(77.88)	92.77(3.08)

Table 4

Reaction Time (in ms) and Accuracy (%) for NA Item Analyses

Task	NA	Reaction Time (SD)	Accuracy(SD)
LDT	High	671.10(55.15)	96.58(5.19)
	Low	703.23(68.94)	91.35(9.35)
Difference		-32.13**	5.40**
SCT	High	763.20(94.21)	95.24(9.99)
	Low	780.77(80.25)	94.13(10.53)
Difference		-17.58	1.11

** $p<.001$

2.3.2 ERP results. The initial mixed ANOVA revealed an interaction of NA and Task ($F(1,40)=5.37$, $p=.03$, $\eta^2_p=.12$), and a main effect of NA ($F(1, 40)=5.31$, $p=.03$, $\eta^2_p=.12$). In order to decompose the interaction, post-hoc analysis were carried for each task separately.

Results for the LDT revealed a main effect of NA, $F(1,20)=11.80$, $p=.003$, $\eta^2_p=.37$) but no interaction with other factors. Low NA words were associated with greater N400 amplitudes than high NA words (see Figure 2). This effect had a central scalp distribution with local maxima at right posterior and frontal sites (see Figure 4), but the interactions between NA and the ROI and Electrode factors were not significant.

There were no main effects of NA, nor interactions with any other factors in the SCT ($F<1$) (see Figure 3). Table 5 displays mean amplitudes at midline electrodes in both tasks.

To summarize, a NA effect was seen only in the LDT with smaller N400 for high than for low NA words. Furthermore, this effect was widespread across all ROIs. No effects were seen in the SCT.

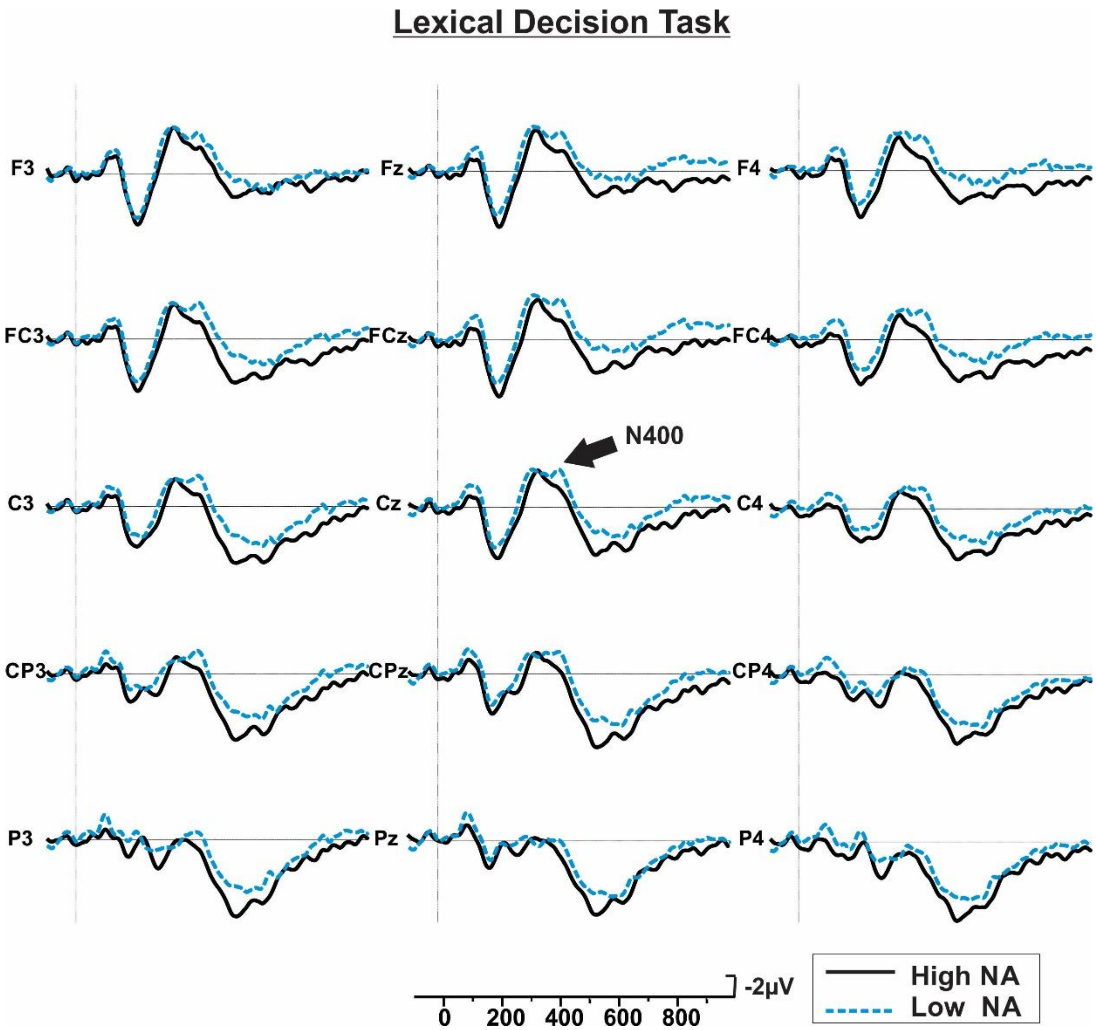

Figure 2. **ERPs for the NA LDT at the Regions of Interest.** N400 effects can be seen starting at around 350 ms post-stimulus interval at all ROIs. Negative is plotted upwards.

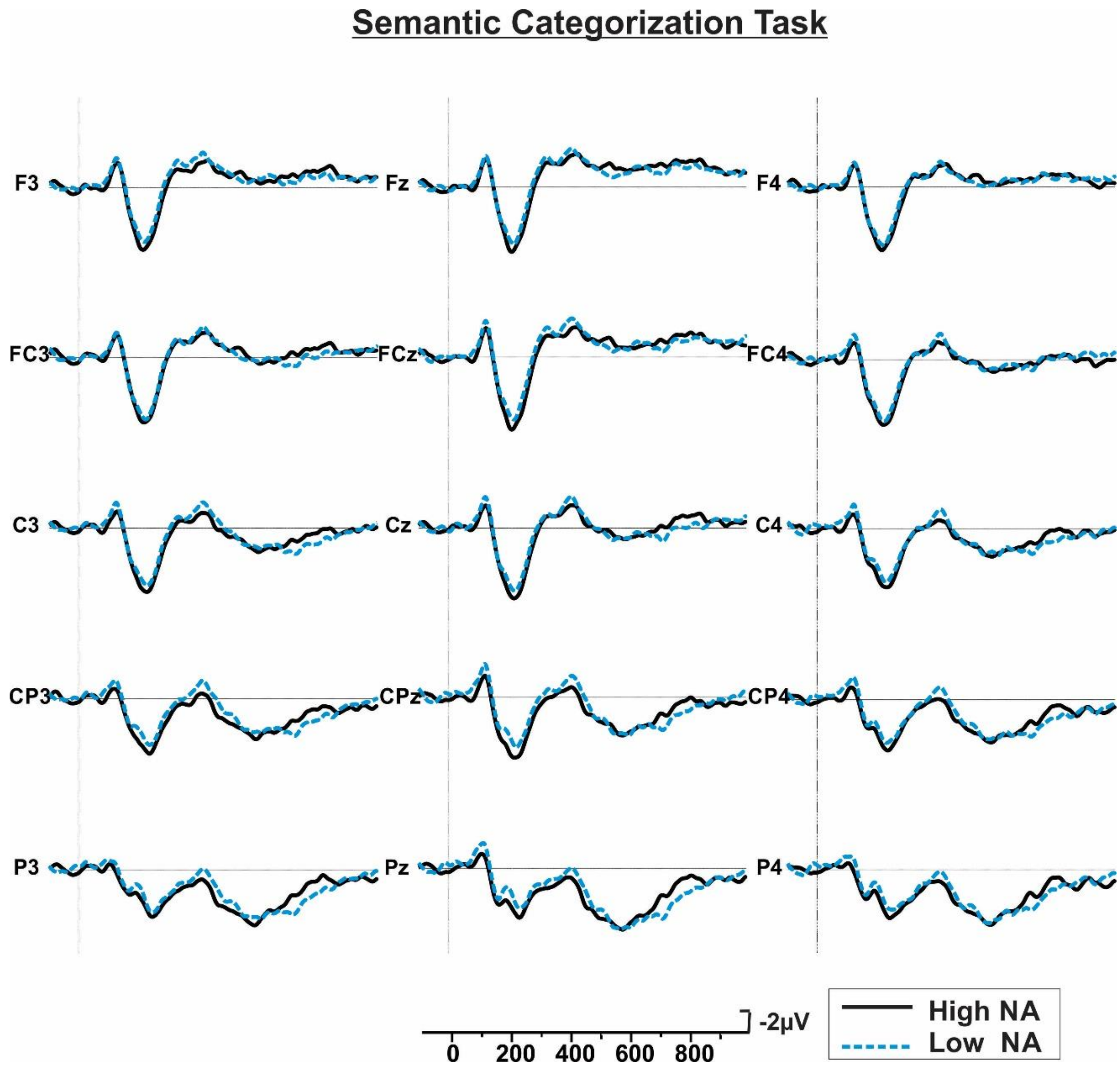

***Figure 3*. ERPs for the NA SCT at the Regions of Interest.** N400 amplitudes do not significantly differ between high and low NA words. Negative is plotted upwards.

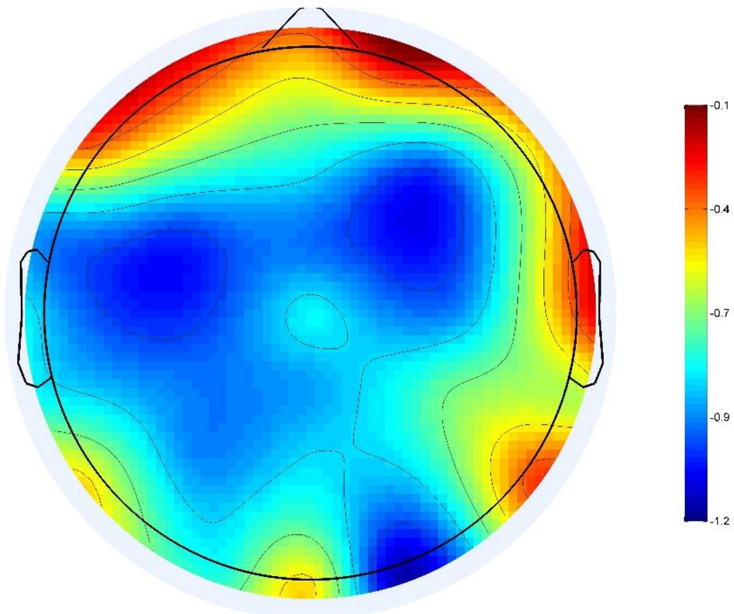

***Figure 4*. Topographic map of NA N400 effect in the LDT.** The effect includes the 350 to 550 ms post-stimulus interval. A central scalp distribution with local maxima at right posterior and frontal sites can be observed.

Table 5

NA N400 Amplitudes (in µV) at Midline Electrodes

Task	**Electrode**	**NA**	**N400(SD)**
LDT	Fz	High	0.19(2.00)
		Low	1.07(2.50)
	FCz	High	0.04(2.07)
		Low	0.97(2.18)
	Cz	High	0.36(2.30)
		Low	0.47(2.08)
	CPz	High	1.46(2.50)
		Low	0.52(2.24)
	Pz	High	2.48(2.74)
		Low	1.60(2.51)
SCT	Fz	High	1.60(2.60)
		Low	1.44(3.00)
	FCz	High	1.38(2.70)
		Low	1.25(3.18)
	Cz	High	0.64(2.64)
		Low	0.55(3.04)
	CPz	High	0.31(2.54)
		Low	0.17(3.22)
	Pz	High	1.60(2.82)
		Low	1.40(3.42)

2.4 Discussion

This chapter investigated the behavioural and N400 effects of NA in a LDT and a SCT. Although accuracy and RT in subject analyses did not differ between high and low NA words, a semantic richness effect was present in item analyses and only during the LDT. More specifically, high NA items were identified as a word more quickly and accurately than low NA items.

N400 ERP analyses revealed that high NA words elicited smaller N400s than low NA words in the LDT across the left, midline and right sites. No N400 differences were seen in the SCT.

Congruency and semantic priming studies have shown that N400 amplitudes are smaller when target words are preceded by an associated word than by an unrelated word (see Kutas & Federmeier, 2011, for a review), suggesting that smaller N400 amplitudes are associated with the ease of processing a word. In an LDT, participants have to decide as quickly as they can whether the presented stimulus is a word or not. This decision may be less effortful for words with many associates because the words associated with them may also become active within the neural semantic network. Activation of these associates may thus allow for more efficient semantic processing: rapid integration of information (semantic associates in this case) that results in easier access to word meaning (Holcomb, 1993; Rugg, 1990), and is reflected in smaller N400 amplitudes. More specifically, the more words associated with a particular target word, the more efficiently the brain can make the decision that the presented stimulus is a word.

These results are in partial agreement with the fMRI study conducted by Pexman and colleagues (2007), who found less activation associated with high than low NA items. Interestingly, Pexman et al. found less activation in areas thought to generate the N400: the left inferior frontal gyrus and the left inferior temporal gyrus (Lau, Phillips, & Poeppel, 2008). One difference is that they found the effect in a SCT where participants were asked to decide whether an item was consumable or not, whereas the effects in this study were observed during lexical decision but not semantic categorization.

Semantic richness is dynamic and its use can be adapted to the type of lexical or semantic task (Yap et al., 2012; Yap et al., 2011). The SCT in this experiment required participants to decide whether an item was living or non-living, which may explain the absence of the semantic richness N400 effect. Certain associates of high NA words may be completely irrelevant or even distracting when trying to make a living/non-living decision. Some living high NA items are associated with non-living words (e.g., “duck” can be associated with “feather”, “rubber”, and “pond”) while some non-living high NA items are associated with living items (e.g., “cage” can be associated with “monkey”, “bird”, and “animals”). Thus, high NA living items may activate attributes/features associated with non-living items and vice-versa. Such information may be detrimental to task performance and thus, NA information may not be actively recruited by the participants in order to perform that task, resulting in a null N400 effect.

Muller et al. (2010) found a larger N400 for high than for low NA words in an LDT, while the opposite effect was evident here. However, in their study, there was a significant difference in imageability ratings ($p<.001$) between high and low NA words. Words with high imageability are processed faster and more accurately than words with low imageability in many tasks, including lexical decision (Cortese, Simpson, & Woolsey, 1997; James, 1975; Kroll & Mervis, 1986; Strain et al., 1995). Furthermore, ERP studies have found that high imageability words elicit a larger N400 than low imageability words (Barber, Otten, Kousta, & Vigliocco, 2013; Gullick, Mitra, & Coch, 2013; Swaab et al., 2002; Welcome, Paivio, McRae, & Joanisse, 2011; West & Holcomb, 2000). Thus, it is not possible to conclude with certainty that RT, accuracy and N400 effects in Muller et al.'s study were due to NA.

Another factor playing a role may be the language the study was conducted in. Muller et al.'s study was conducted in Spanish; thus, they used a different set of norms. More studies in Spanish are needed in order to replicate their findings. It would be interesting to perform a study with two language groups (i.e., Spanish vs. English) to investigate whether the effects are similar or differ according to language. Nelson, McEvoy and Schreiber (2004) bring to our attention that NA norms are a construction of lexical knowledge associated to a group of persons that share language and culture. Thus, it is important to keep in mind that results might not always generalize to the whole population. For example, large differences were observed even when comparing norms derived from American and Great Britain English (Nelson et al., 2004). Differences may even be greater when comparing norms from different languages. For example, number of associates for a particular word may differ in a language with transparent orthography (i.e., one-to-one letter to phoneme correspondence) such as Spanish relative to English, which is a language with deep orthography. In turn, differences in number of associates as function of language may yield distinct interactions between semantic richness effects and task demands.

Laszlo and Federmeier (2012) also found that N400 amplitudes were greater for high than low NA words. One difference is that Laszlo and Federmeier's participants performed a word recognition task where they only had to respond to filler items and not to the experimental items (i.e., they had to identify proper names) because the researchers aimed at investigating ERP correlates of NA free from any lexical or semantic decision. As previously mentioned, there is behavioural evidence that semantic richness variables are dynamic: they can yield facilitatory effects during some tasks but not others. Thus, it is possible that the N400 effect would present a different profile in passive tasks, where experimental items do not require a response, than in active tasks, where experimental items do require a response, such as LDT.

Finally, Rabovsky et al. (2012) found an N400 effect with the variable number of features (NoF) but not of NA, while carefully controlling for both. Although NoF was partially controlled in this thesis (norms were not available for all items), the mean difference between high and low NA words in Rabovsky et al. was nine while in the present experiment, the mean was almost 15. Thus, it is possible that their NA high/low manipulation was not large enough to detect an effect. In light of the conflicting ERP results and the important methodological differences among all the studies, more neuroimaging experiments are needed in order to clarify the neural correlates of NA and its dynamics with task demands.

In sum, item analyses yielded more accurate and faster RTs for high than low NA words but only during LDT. ERP differences were also detected, with smaller N400 for high than low NA words –at frontal, central and parietal sites– during LDT but not during SCT. This results suggest that NA is a semantic richness variable that can be dynamically shaped by task demands. Future studies should aim at investigating the effect during SCTs where NA information may be advantageous.

Chapter 3: Semantic Neighbours

3.1 Background and Hypotheses

Similar to studies investigating number of associates, studies researching semantic neighbourhood effects have found that words with large neighborhoods are recognized more quickly and accurately than words with small neighbourhoods. Consistent results have been found in lexical decision tasks (Buchanan et al., 2001; Pexman et al., 2008; Yap et al., 2012; Yap et al., 2011) but there is no agreement as to the effects in semantic categorization tasks. Some studies have not found an effect when other variables were accounted for (Pexman et al., 2008; Yap et al., 2012; Yap et al., 2011) while others have found it in a modified version of a semantic categorization task where participants had to overtly respond only to the experimental items (Siakaluk et al., 2003).

This is the first ERP study investigating the effect of this dimension during single visual word recognition. Following the same rationale as the experiment with the NA dimension (chapter 2), I hypothesized that words with high number of semantic neighbours (NSN) would be recognized faster than words with low NSN in both tasks. Furthermore, I hypothesized smaller N400 amplitudes for high than for low NSN words in both tasks. Finally, I expected that these effects would be larger in the SCT than LDT.

3.2 Methods

The participants were the same as in the NA experiment. Thus, to avoid repetition effects, the stimuli in this experiment were different from the stimuli in the NA experiment. The testing protocol, experimental tasks and EEG recording are identical to the ones described in the methods section of chapter 2 (pp. 44-45, 49), with the exception that the experimental items differed by NSN.

3.2.1 Stimuli. As in the NA Experiment, word stimuli in both the LDT and SCT were identical and consisted of a total of 120 words. They were chosen based on two conditions: high NSN (60 items) and low NSN (60 items). Number of semantic neighbours was determined using the number of global neighbours from the University of Windsor database's Wordmine2 Free (Durda & Buchanan, 2006). The variables controlled for were word length, word frequency (HAL frequency), orthographic neighbourhood density and bigram frequency by position (the English Lexicon Project) (Balota et al., 2007), concreteness, familiarity, and imageability (MRC Psycholinguistic Database) (Coltheart, 1981). Where data were available, they were also controlled for NoF (McRae et al., 2005), NA (Nelson et al., 1998), and BOI (Bennett et al., 2011; Tillotson et al., 2008). Semantic and lexical characteristics are provided in table 6.

In the LDT, 120 pseudowords were generated using the English Lexicon Project (Balota et al., 2007) and were matched to the real words in length, orthographic neighbourhood density and bigram frequency by position. Living and non-living words were also controlled for all the variables mentioned above. The semantic and lexical characteristics of the living and non-living items are provided in table 7.

Table 6

NSN Stimuli Characteristics

Variables	**NSN**		**p-value**	**Pseudoword (SD)**	**p-value (NA vs Pseudoword)**
	High(SD)	**Low(SD)**			
Number of Semantic Neighbours	11.67(6.60)	1.90(0.93)	<.001		
Word Length	5.33(1.68)	5.50(0.93)	.63	5.40(1.67)	.97
Frequency (log HAL)	8.30(1.40)	8.12(1.75)	.78		
Orthographic Neighbourhood Density	6.27(6.48)	6.10(7.89)	.90	6.18(6.63)	.90
Bigram Frequency	2863.40(1509.20)	3085.80(1615.10)	.44	2698.40(1080.22)	.12
Concreteness	605.91(20.68)[a]	610.82(19.88)[b]	.24		
Familiarity	535.22(60.37)[c]	520.83(55.58)[d]	.22		
Imageability	593.70(29.43)[a]	594.22(23.35)[b]	.92		
Number of Features	15.25(9.03)[e]	14.09(5.67)[f]	.45		
Number of Associates	24.50(29.26)[g]	19.46(26.33)[d]	.35		
Body-Object Interaction	5.16(0.76)[h]	4.91(0.85)[i]	.11		

a=available for 46 items, b=available for 51 items, c=available for 46 items, d=available for 52 items, e=available for 55 items, f=available for 45 items, g=available for 56 items, h=available for 48 items, i=available for 59 items,

Table 7

NSN Living-Non Living Items Characteristics

Variables	Living	Non-Living	p-value
Number of Semantic Neighbours	6.71(6.68)	6.87(6.94)	.90
Word Length	5.33(1.82)	5.51(1.61)	.58
Frequency (log HAL)	8.00(1.44)	8.39(1.32)	.12
Orthographic Neighbourhood Density	6.38(7.63)	5.95(6.82)	.74
Bigram Frequency	2749.51(1493.27)	3175.82(1618.78)	.14
Concreteness	610.25(21.77)[a]	606.78(18.84)[b]	.40
Familiarity	517.97(54.74)[b]	537.18(60.17)[b]	.10
Imageability	598.40(24.85)[a]	589.63(27.11)[b]	.10
Number of Features	13.90(6.92)[b]	15.46(8.37)[c]	.30
Number of Associates	20.87(29.91)[c]	23.24(25.97)[d]	.66
Body-Object Interaction	4.89(0.77)[e]	5.15(0.85)[d]	.10

a=available for 48 items, b=available for 49 items, c=available for 53 items, d=available for 55 items, e=available for 52 items.

3.2.2. Statistical analyses. All data was analyzed with the Statistical Package for the Social Sciences v. 20 (SPSS), (IBM, Armonk, NY, USA).

3.2.2.1 Behavioural performance. Trials with reaction times (RT) exceeding ±2.5 standard deviations from the mean were excluded as outliers. Accuracy and RT were analyzed in two separate 2X2 Mixed ANOVAs with the within-subject factor NSN (high, low) and between-subject factor Task (LDT and SCT).

In addition, independent sample t-tests item analyses for both accuracy and RT were performed for each task with high vs. low NSN as the independent variable.

3.2.2.2 ERP data. Electrode sites were grouped into 3 regions of interest (ROIs) that included 5 electrodes each: left lateral (F3, FC3, C3, CP3, P3), midline (Fz, FCz, Cz, CPz, Pz), and right lateral (F4, FC4, C4, CP4, P4). Mean amplitudes from 350 to 550 ms post-stimulus were chosen for analyses. A mixed ANOVA was conducted with the following within-subject factors: NSN (2 levels), Electrode (5 levels), ROI (3 levels) and the between-subject factor Task (LDT vs. SCT)[2]. Interactions involving the factor Task were decomposed with repeated measures ANOVAs on each Task with the factors NSN, Electrode and ROI. When interactions were significant within a task, additional post-hoc tests with Fisher's Least Significance Difference (LSD) pairwise comparisons were carried. A Greenhouse-Geisser correction procedure was used for all ERP analyses when sphericity was violated (Geisser & Greenhouse, 1958); uncorrected degrees of freedom are reported, as per convention.

[2] Analyses were also carried with an additional factor Time (4 levels) consisting of mean amplitudes of the following 50 ms bins: 350-400, 400-450, 450-500 and 500-550. The Time factor, however, did not interact with NSN or Task, and thus did not yield additional information. Therefore, only analyses using the whole interval mean amplitude are reported (i.e., without the Time factor).

3.3 Results

One participant from the LDT and one from the SCT group were excluded from all analyses due to noisy EEG data. Thus, there was a final sample of 23 participants in each group.

2.3.1 Behavioural results. In the LDT, 2.7% of trials were excluded as outliers while 2.6% were excluded in the SCT.

Reaction time analyses did not reveal a significant main effect of NSN ($F<1$), nor an interaction between NSN and Task ($F(1,44)=1.94$, $p=.17$). Similar results were obtained for Accuracy analyses ($F<1$). Results are summarized in table 8.

Item analyses also did not reveal significant accuracy ($t(118)=1.67$, $p=.10$) or reaction time differences between high and low NSN items ($t(118)=-.70$, $p=.50$) during the LDT. Similarly, no accuracy ($t(118)=.83$, $p=.41$) or reaction time differences ($t(118)=.00$, $p=.99$) for high and low NSN items were detected during the SCT. Results are summarized in table 9.

Table 8

Reaction Time (in ms) and Accuracy (%) for NSN Subject Analyses

Task	NSN	Reaction Time (SD)	Accuracy %(SD)
LDT	High	711.50(98.91)	93.11(5.28)
	Low	704.62(100.27)	92.10(6.95)
SCT	High	731.05(76.65)	93.62(3.75)
	Low	749.72(87.40)	92.00(3.96)

Table 9

Reaction Time (in ms) and Accuracy (%) for NA Item Analyses

Task	NSN	Reaction Time (SD)	Accuracy %(SD)
LDT	High	661.61(70.26)	96.52(5.36)
	Low	670.71(73.96)	93.84(11.22)
SCT	High	767.22(109.00)	93.77(12.62)
	Low	767.20(88.35)	91.74.(14.00)

3.3.2 ERP results. The initial mixed ANOVA revealed a significant interaction of NSN and Electrode ($F(4, 176)=8.13$, $p=.002$, $\eta^2_p=.16$) and a 4-way interaction between NSN, Task, ROI and Electrode that was approaching significance ($F(8, 352)=2.11$, $p=.06$, $\eta^2_p=.05$). Thus, ANOVAS were carried out for each task separately.

In the LDT, results revealed an interaction between NSN and Electrode ($F(4, 88)=3.65$, $p=.05$, $\eta^2_p=.14$). Post-hoc LSD comparisons revealed that low NA words were associated with larger N400 amplitudes than high NA words at electrodes C3, Cz , C4 ($p=.03$, $\eta^2_p=.20$), CP3, CPz, CP4 ($p=.02$, $\eta^2_p=.22$), and P3, Pz, P4 ($p=.01$, $\eta^2_p=.27$) (See Figure 5). This effect had a centro-posterior scalp distribution with local maxima at right posterior sites (see Figure 7).

Analyses of the SCT also revealed an interaction of NSN with Electrode ($F(4, 88)=5.85$, $p=.004$, $\eta^2_p=.21$). However, post-hoc LSD comparisons revealed no significant differences between high and low NSN words (all $p>.13$) (see Figure 6). Refer to table 10 for mean amplitudes at midline electrodes in both tasks.

In summary, smaller N400 amplitudes were seen for high NSN than for low NSN words in the LDT at centro-posterior electrodes. N400 amplitudes were not significantly different in the SCT.

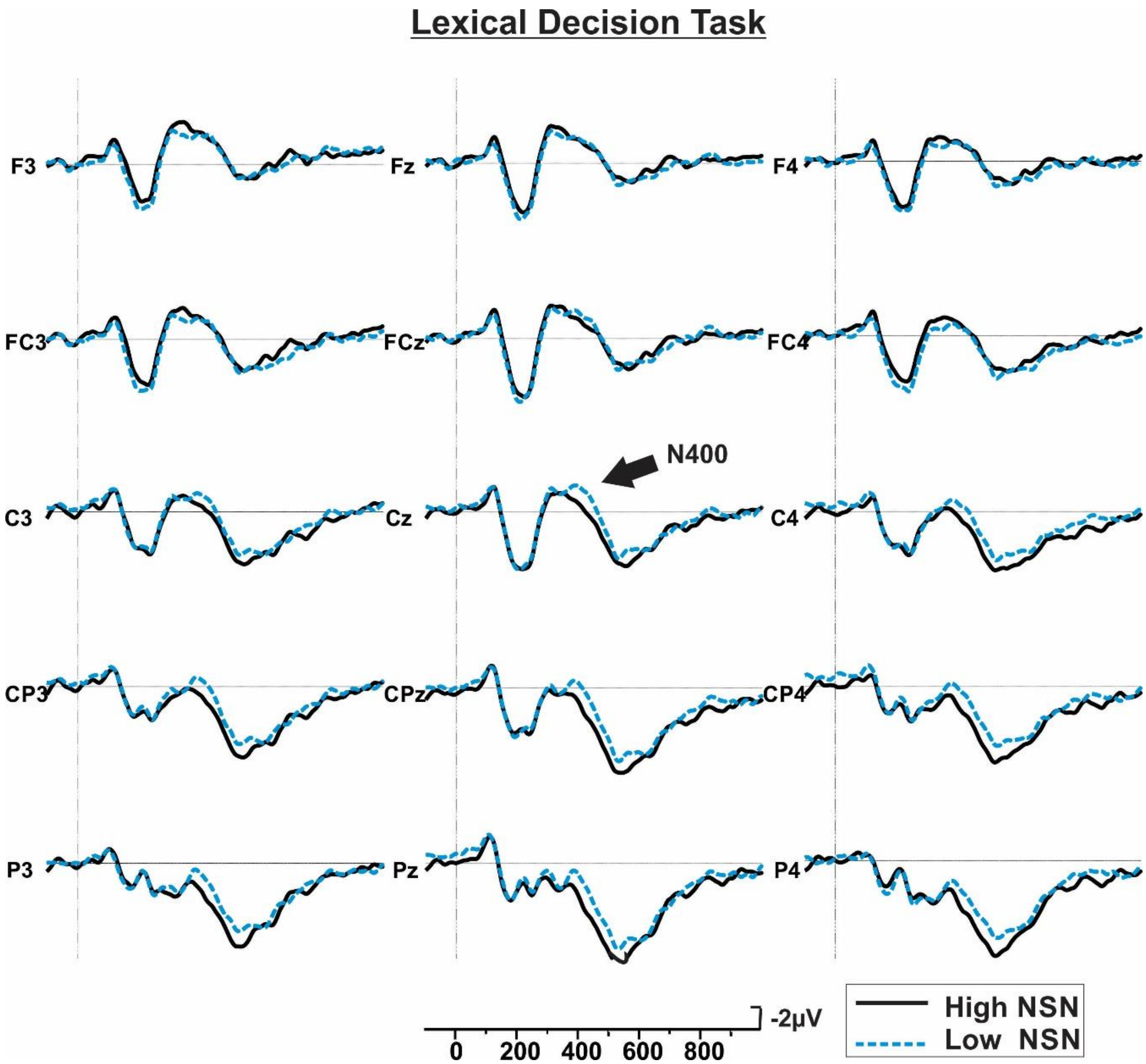

***Figure 5*. ERPs for the NSN LDT at the Regions of Interest.** N400 effects can be seen starting at around 350 ms post-stimulus interval at centro-posterior electrodes. Negative is plotted upwards.

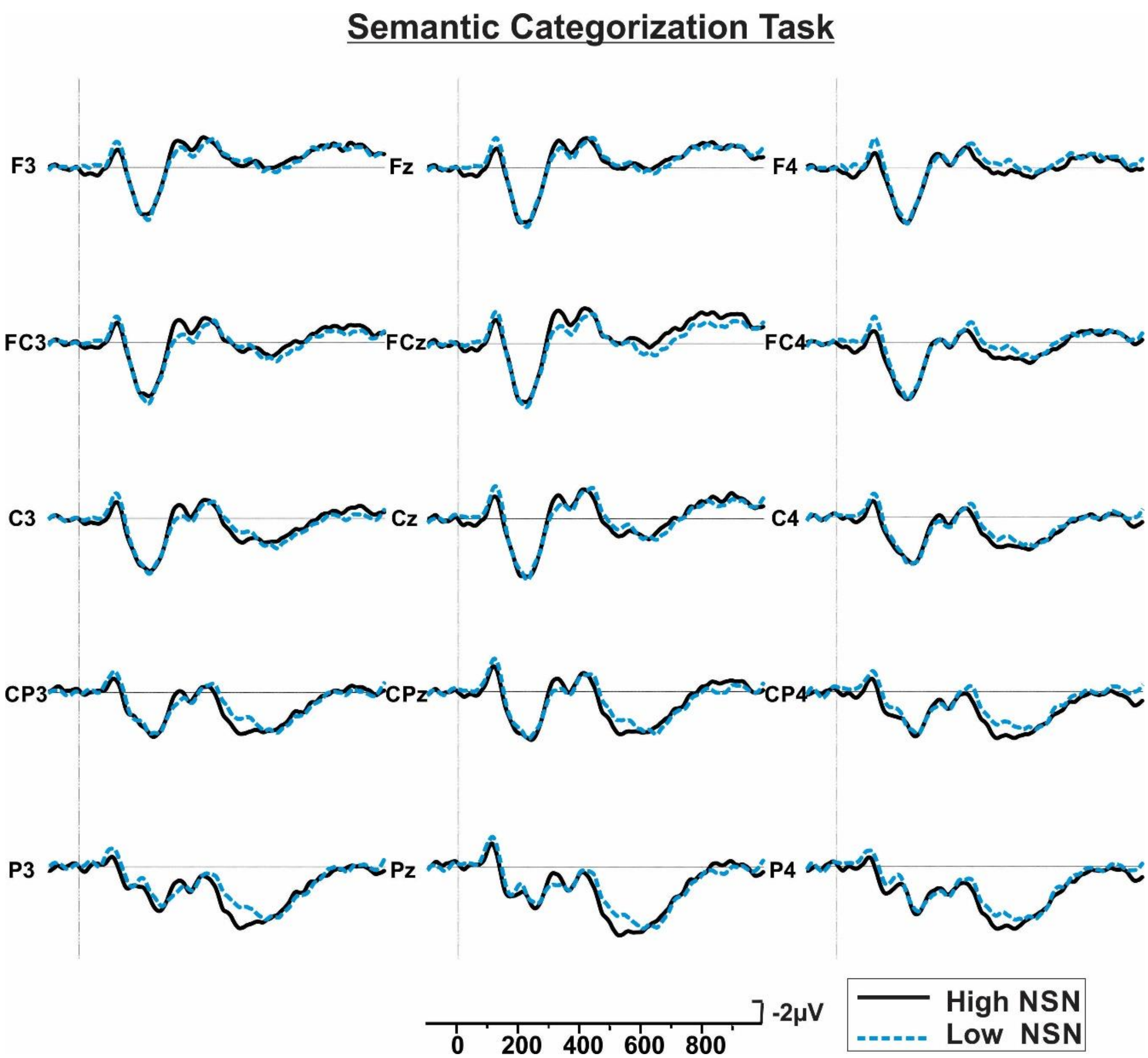

Figure 6. **ERPs for the NSN SCT at the Regions of Interest.** N400 amplitudes do not significantly differ between high and low NSN words. Negative is plotted upwards.

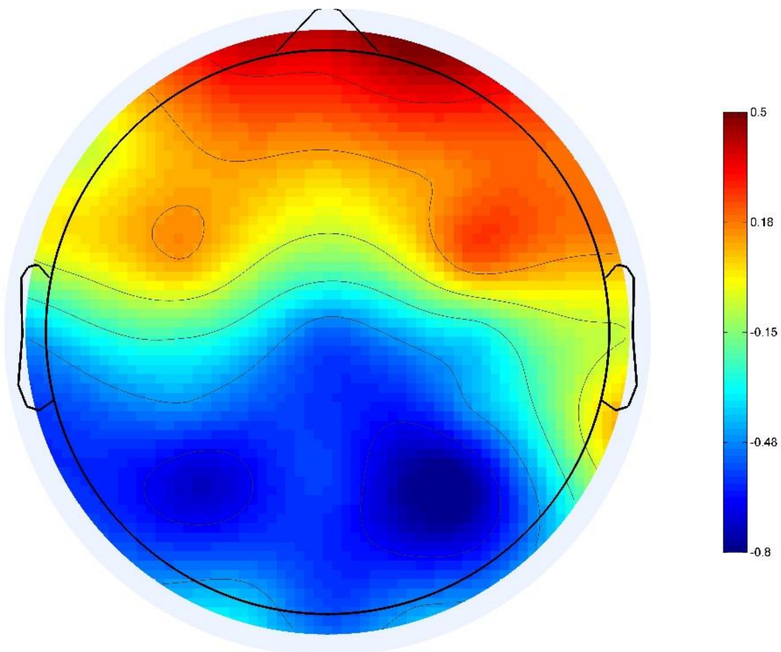

***Figure 7*. Topographic map of N400 NSN effect in the LDT.** The effect includes the 350 to 550 ms post-stimulus interval. The effect is seen at centro-posterior sites with local maxima at right posterior electrodes.

Table 10

NSN N400 Amplitudes (in μV) at Midline Electrodes

Task	**Electrode**	**NSN**	**N400(SD)**
LDT	Fz	High	-0.51(2.44)
		Low	-0.60(2.25)
	FCz	High	-0.16(2.34)
		Low	-0.38(2.33)
	Cz	High	0.74(2.52)
		Low	0.19(2.50)
	CPz	High	2.04(2.60)
		Low	1.42(2.65)
	Pz	High	3.31(2.87)
		Low	2.73(2.84)
SCT	Fz	High	-0.81(3.39)
		Low	-0.77(3.27)
	FCz	High	-0.94(3.85)
		Low	-0.73(3.47)
	Cz	High	-0.29(4.00)
		Low	-0.57(3.71)
	CPz	High	0.57(4.16)
		Low	0.19(3.60)
	Pz	High	2.17(4.50)
		Low	1.46(3.73)

3.4 Discussion

Contrary to previous LDT studies, subject and item analyses did not reveal a reaction time advantage for high NSN relative to low NSN items. This discrepancy, however, may be explained by several factors.

There is no agreement as to which measure best captures semantic neighbourhood size. This problem is reflected in the various measures that studies used to investigate its effects on semantic processing. For example, Yap et al. (2011) used a measure called *mean semantic similarity-5000,* which reflects the mean cosine similarity between a target word and its closest 5000 neighbours in a high dimensional semantic space. In a later study (2012), they used semantic neighbourhood values as measured by the average to radius of co-occurrence (ARC) (Shaoul & Westbury, 2010). Buchanan et al. (2001) used the *mean semantic distance* from the Hyperspace Analogue to Language Model (HAL), which is based on a 10-word moving window for computing global co-occurrence (Lund & Burgess, 1996) while Mirman and Magnuson (2008) used measures from the Correlated Occurrence Analogue to Lexical Semantic Model (COALS) that included the *correlated occurrence analogue to lexical semantic* (Rohde, Gonnerman, & Plaut, 2005) and *the mean semantic distance* based on a 10-word moving window for computing global co-occurrence. Finally, Pexman et al. (2008) used number of semantic neighbours or NSN (Durda & Buchanan, 2008), a measure from the WINDSORS model that simply counts the number of neighbours of a word within a specified radius in semantic space. The WINDSORS model is thought to be an improved measure of semantic neighbourhood size as they are free from the influences of word frequency effects (a weakness of the HAL model, for example). Recall that word frequency facilitatory effects are ubiquitous in word recognition (e.g., Andrews & Heathcote, 2001; Monsell et al., 1989), and can explain a considerable amount of variance (about 40%) in LDTs and SCTs (e.g., Balota et al., 2004; Yap et al., 2012). Thus, some of the results in the literature may have been confounded by word frequency effects. In order to avoid this problem, the NSN measure from the WINDSORS model was used in this experiment while controlling for other semantic richness variables.

The ERP technique becomes valuable when behavioural effects are small or non-existent, because it allows the detection of processing differences that are not detectable with simple reaction time measures. Although no significant reaction time advantage was detected, smaller N400s were elicited by high than low NSN words. Similar to the NA experiment in Chapter 2, I found significantly smaller N400 amplitudes for high than low NSN words in the LDT, but not in the SCT. A number of researchers consider that measures such as semantic neighbourhood size and number of associates are measures of semantic relatedness (Buchanan et al., 2001; Locker et al., 2003; Mirman & Magnuson, 2008) albeit through different approaches (statistical co-ocurrence vs. word association). Thus, it is possible that both NA and NSN reflect similar underlying neural mechanisms. If both measures reflect similar underlying mechanisms, then I would expect to find similar neurophysiological results in the NA and NSN experiments. This is indeed what I found: in both the NA and the NSN experiments, the N400 effect was only seen in the LDT, and there were no ERP differences in the SCT. Thus, similarly to NA, the findings for NSN may be explained by the type of semantic neighbours under examination. NSN reflects the number of semantic neighbours of a word based on context co-occurrence. It is possible that some neighbours that occur within a particular context are not necessarily helpful when making a living/non-living decision, and such information may not be actively recruited if it is distracting or not helpful.

The N400 associated with high NSN words may reflect more efficiency when processing the word during a word/nonword decision. Thus, the mechanisms utilized during processing of these words seem to be similar in both NA and NSN. However, the topographic distribution of NSN was very different from that of NA, which showed a more widespread distribution (see Figures 4 and 7). Clearly, despite the effect being similar, both measures are not identical. Future studies should comparatively investigate these dimensions with fMRI or MEG imaging techniques in order to localize their effects.

Chapter 4: Body-Object Interaction

4.1 Background and Hypotheses

Visual word recognition studies have shown that words with high BOI rating are recognized more quickly and accurately than words with low BOI rating. The effect has been observed in both lexical decision and in imageable/not imageable semantic categorization tasks. (Bennett et al., 2011; Siakaluk, Pexman, Aguilera, et al., 2008; Siakaluk, Pexman, Sears, et al., 2008; Tillotson et al., 2008; Wellsby et al., 2011; Yap et al., 2012). In addition, different performance effects were observed when task instructions changed despite employing the same set of high and low BOI words (Tousignant & Pexman, 2012), suggesting that participants exert top-down control based on the available context information.

Only one neuroimaging study has investigated the effects of BOI, which found that high BOI words elicited more activation than low BOI words in the left supramarginal gyrus, an area thought to be involved in goal-oriented hand-object interaction (Hargreaves et al., 2012). This is the first ERP study to investigate body-object interaction effects. I hypothesized that high BOI words would yield shorter reaction times than low BOI words both during LDT and SCT. Furthermore, I expected smaller N400 amplitudes for high than low BOI words during both tasks. Finally, I hypothesized that behavioural and N400 effects would be larger in the SCT than in the LDT.

4.2 Methods

The participants were the same as in the NA and NSN experiments. The stimuli in this experiment were therefore different than the ones employed in the previous experiments. The testing protocol, experimental tasks and EEG recording are identical to the ones described in the methods section of chapter 2 (pp. 44-45, 49), with the exception that the experimental items differed by BOI.

4.2.1 Stimuli. Similar to the experiments described in chapters 2 and 3, word stimuli in both the LDT and SCT were identical and consisted of a total of 120 words. Words were chosen based on two conditions: high BOI (60) and low BOI (60). BOI ratings were determined using the norms established by Siakaluk and colleagues (Bennett et al., 2011; Tillotson et al., 2008).

The variables controlled for were word length, word frequency (HAL frequency), orthographic neighbourhood density and bigram frequency by position (the English Lexicon Project) (Balota et al., 2007), concreteness, familiarity, and imageability (MRC Psycholinguistic Database) (Coltheart, 1981). Where data were available, they were also controlled for NoF (McRae et al., 2005), NA (Nelson et al., 1998), and NSN (Durda & Buchanan, 2006).

In the LDT, 120 pseudowords were generated using the English Lexicon Project (Balota et al., 2007) and were matched to the real words in length, orthographic neighbourhood density and bigram frequency by position. Living and non-living words were also balanced for all the variables mentioned above. The semantic and lexical characteristics items are provided in tables 11 and 12.

Table 11

BOI Stimuli Characteristics

Variables	BOI		p-value	Pseudoword (SD)	p-value (BOI vs Pseudoword)
	High(SD)	Low(SD)			
Body-Object Interaction	5.00(0.49)	2.58(0.61)	<.001		
Word Length	6.50(2.38)	6.68(1.61)	.57	6.67(1.64)	.73
Frequency (log HAL)	7.56(1.20)	7.64(1.40)	.72		
Orthographic Neighbourhood Density	3.15(6.03)	1.95(3.38)	.18	2.63(4.56)	.90
Bigram Frequency	3077.40(1598.11)	3394.43(1551.63)	.28	3273.60(1155.07)	.84
Concreteness	603.45(28.20)[a]	593.49(26.95)[b]	.11		
Familiarity	516.13(52.26)[c]	500.0(42.0)[d]	.13		
Imageability	597.72(38.03)[e]	591.86(33.67)[f]	.47		
Number of Features	13.08(5.04)[g]	13.21(3.01)[h]	.90		
Number of Semantic Neighbours	2.62(2.40)[i]	2.50(4.55)	.86		
Number of Associates	11.06(9.07)[j]	8.24(7.87)[k]	.10		

a=available for 42 items, b=available for 37 items, c=available for 47 items, d= available for 38 items, e=available for 43 items, f=available for 37 items, g=available for 34 items, h=available for 28 items, i=available for 58 items, j=available for 49 items, k=available for 50 items

Table 12

BOI Living and Non-Living Items Characteristics

Variables	Living(SD)	Non-Living(SD)	p-value
Body-Object Interaction	3.63(1.40)	3.96(1.25)	.18
Word Length	6.45(1.75)	6.73(1.74)	.38
Frequency (log HAL)	7.49(1.76)	7.74(1.5)	.27
Orthographic Neighbourhood Density	2.92(5.98)	2.18(3.52)	.41
Bigram Frequency	3129.10(1511.83)	3342.72(1644.30)	.46
Concreteness	602.71(29.88)[a]	595.15(25.75)[b]	.23
Familiarity	507.64(49.06)[c]	509.23(47.98)[d]	.88
Imageability	601.47(38.63)[a]	589.17(32.76)[e]	.13
Number of Features	13.48(3.52)[f]	12.80(4.84)[f]	.53
Number of Semantic Neighbours	2.37(2.28)	2.76(4.67)[g]	.56
Number of Associates	10.65(8.99)[h]	8.69(8.12)[i]	.26

a=available for 38 items, b=available for 41 items, c=available for 39 items, d=available for 47 items, e=available for 42 items, f=available for 31 items, g=available for 58 items, h=available for 48 items, i=available for 51 items.

4.2.2 Statistical analyses. All data was analyzed with the Statistical Package for the Social Sciences v. 20 (SPSS), (IBM, Armonk, NY, USA).

4.2.2.1 Behavioural performance. Trials with reaction times (RTs) exceeding ±2.5 standard deviations from the mean were excluded as outliers. Accuracy and RT were analyzed in two separate 2X2 Mixed ANOVAs with the within-subject factor BOI (high, low) and between-subject factor Task (LDT, SCT).

In addition, independent sample t-tests item analyses for both accuracy and RT were performed for each task with high vs. low BOI as the independent variable.

3.2.2.2 ERP data. Electrode sites were grouped into 3 regions of interest (ROIs) that included 5 electrodes each: left lateral (F3, FC3, C3, CP3, P3), midline (Fz, FCz, Cz, CPz, Pz), and right lateral (F4, FC4, C4, CP4, P4). Mean amplitudes from 350 to 550 ms post-stimulus were chosen for analyses. A mixed ANOVA was conducted with the following within-subject factors: BOI (2 levels), Electrode (5 levels), ROI (3 levels) and the between-subject factor Task (LDT vs. SCT). Interactions involving the factor Task were decomposed with repeated measures ANOVAs on each Task with the factors BOI, Electrode and ROI. When interactions were significant within a task, additional post-hoc tests with Fisher's Least Significance Difference (LSD) pairwise comparisons were carried. A Greenhouse-Geisser correction procedure was used for all ERP analyses when sphericity was violated (Geisser & Greenhouse, 1958). As per convention, uncorrected degrees of freedom are reported.

4.3 Results

In the LDT, 2.6% of trials were excluded as outliers, while 2.4% were excluded in the SCT.

4.3.1 Behavioural performance. Reaction time analyses revealed a significant interaction between BOI and Task ($F(1,43)=4.11$, $p=.05$, $\eta^2_p=.09$). However, post-hoc LSD comparisons of BOI at each task did not reach statistical significance (all $p>.90$). Similarly, no significant main effects or interactions were observed in accuracy analyses (all $p>.4$). Mean values are provided in table 13.

Item analyses independent sample t-tests performed for each task revealed that high BOI items were recognized faster than low BOI items in the LDT ($t(114.42)=-2.34$, $p=.02$, $d=.43$), while accuracy results were not significant ($t(118)=.70$, $p=.49$). Accuracy and RT did not significantly differ between high and low BOI words in the SCT (all $p>.45$). Mean accuracy and reaction time by condition are provided in table 14.

Table 13

Reaction Time (in ms) and Accuracy (%) for BOI Subject Analyses

Task	**BOI**	**Reaction Time (SD)**	**Accuracy %(SD)**
LDT	High	757.43(121.74)	93.48(5.05)
	Low	770.49(116.78)	93.00(6.93)
SCT	High	780.44(111.00)	93.48(3.08)
	Low	759.05(84.58)	94.02(3.44)

Table 14

Reaction Time (in ms) and Accuracy (%) for BOI Item Analyses

Task	BOI	Reaction Time (SD)	Accuracy(SD)
LDT	High	693.23(63.50)	96.09(5.97)
	Low	723.15(75.94)	95.36(5.36)
Difference		-29.91*	.72
SCT	High	800.88(85.82)	93.62(12.54)
	Low	788.06(96.70)	94.13(11.32)
Difference		-12.81	-.51

* p<.05

4.3.2 ERP results. Initial ANOVA analyses revealed a 3-way interaction of BOI, Task and ROI ($F(2, 88)=5.41$, $p=.007$, $\eta^2_p=.11$). Thus, post-hoc repeated measures ANOVAs were carried out for each task separately. Results for the LDT revealed no significant interactions nor main effects involving BOI ($F<1$), while results for the SCT revealed a significant interaction between BOI and ROI ($F(2, 44)=4.15$, $p=.04$, $\eta^2_p=.16$). However, post-hoc LSD comparisons at each ROI did not yield significant differences between high and low BOI words (all $p>.63$). Grand averages for the LDT are shown in Figure 8 and for the SCT in Figure 9. Mean amplitudes at midline electrodes are shown in table 15.

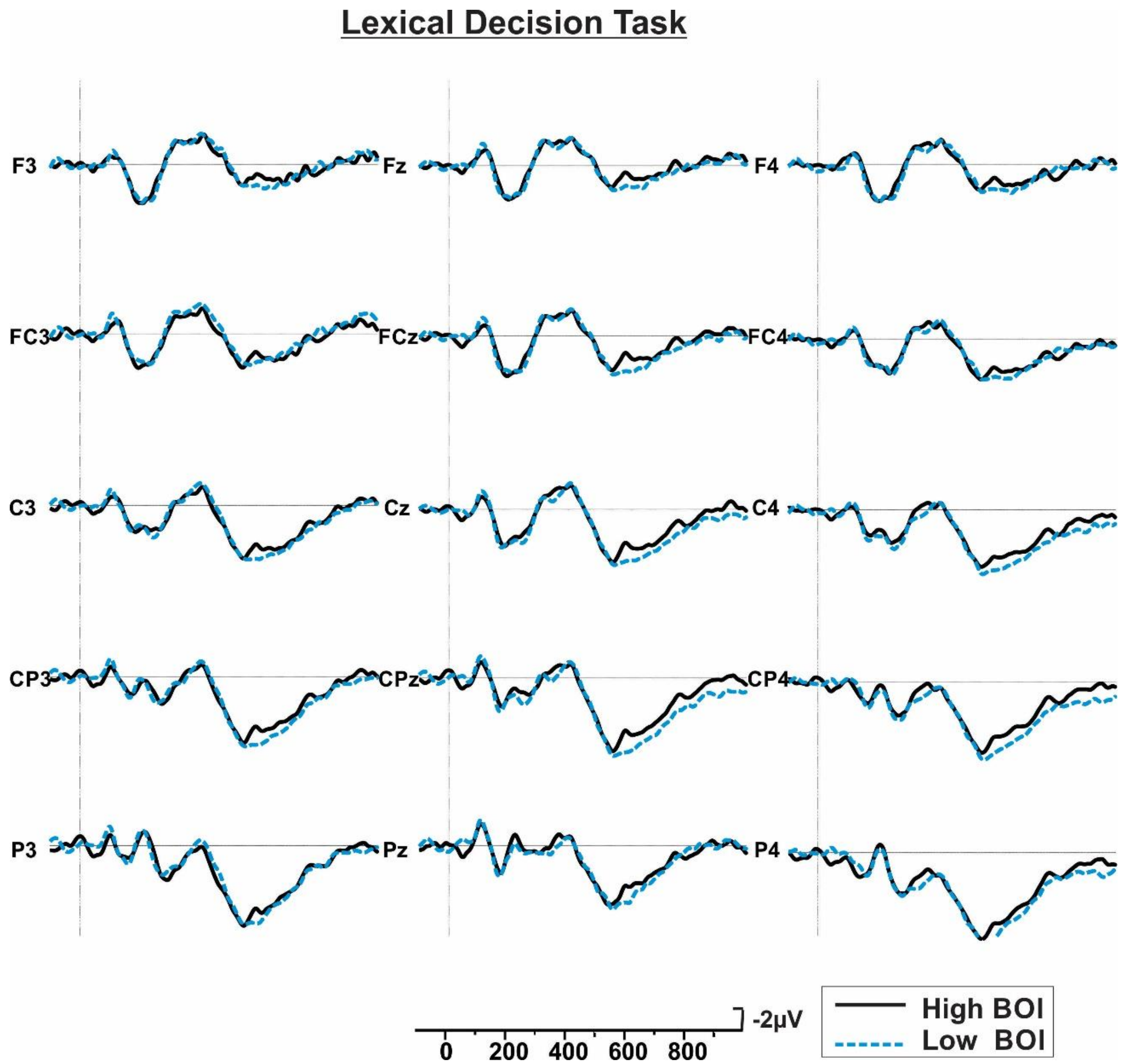

***Figure 8*. ERPs for the BOI LDT at the Regions of Interest**. N400 amplitudes do not significantly differ between high and low BOI words. Negative is plotted upwards.

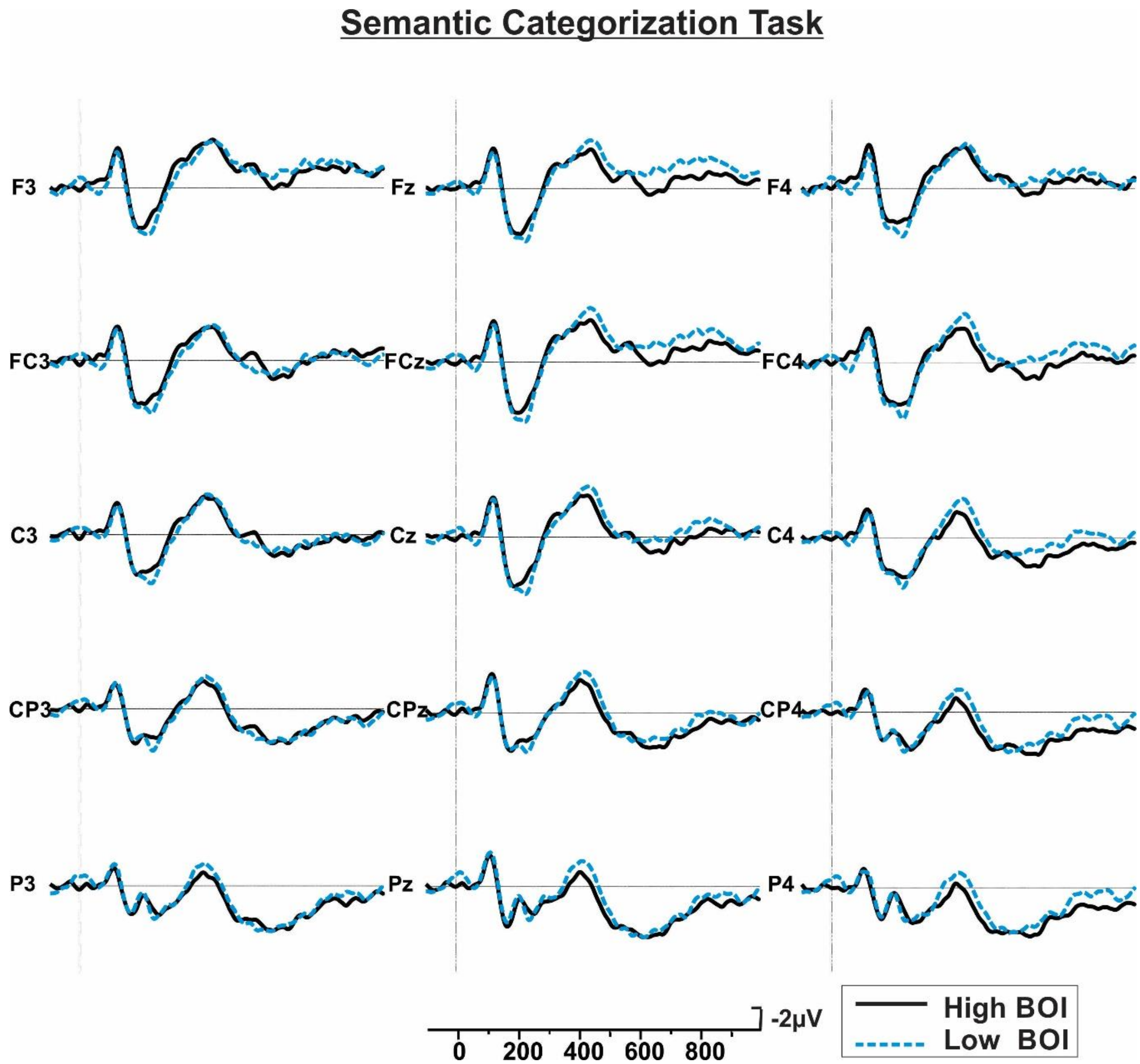

***Figure 9*. ERPs for the BOI SCT at the Regions of Interest**. N400 amplitudes do not significantly differ between high and low BOI words. Negative is plotted upwards.

Table 15

BOI N400 Amplitudes (in µV) at Midline Electrodes

Task	Electrode	BOI	N400(SD)
LDT	Fz	High	-0.53(2.90)
		Low	-0.51(2.72)
	FCz	High	-0.14(3.44)
		Low	-0.18(3.00)
	Cz	High	0.27(3.57)
		Low	0.30(3.53)
	CPz	High	1.08(3.59)
		Low	1.14(3.69)
	Pz	High	1.14(3.81)
		Low	1.19(4.26)
SCT	Fz	High	-1.45(2.89)
		Low	-1.57(3.06)
	FCz	High	-1.60(2.99)
		Low	-1.77(3.14)
	Cz	High	-1.37(3.00)
		Low	-1.44(3.28)
	CPz	High	-0.61(3.04)
		Low	-0.78(3.37)
	Pz	High	0.61(3.31)
		Low	0.27(3.75)

4.4 Discussion

No significant behavioural differences were detected in the LDT in subject analyses. However, in item analyses, high BOI words were processed significantly more quickly than low BOI words. BOI effects during SCT were non-significant in both subject and item analyses. Although other studies have found facilitatory effects of BOI in SCT, their tasks required different decisions, including differentiation between action and entity words (Tousignant & Pexman, 2012), and between concrete and abstract words, or a decision as to the word's degree of imageability (Siakaluk et al., 2003; Wellsby et al., 2011; Yap et al., 2012). This suggests that, similar to other semantic richness variables, BOI is a dynamic variable that may exert a facilitatory, inhibitory or null effect depending on task demands. The behavioural effects observed during item analyses are partially consistent with Perceptual Symbol System (PSS) theory (Barsalou, 1999, 2003; Barsalou et al., 2003), which purports that sensory, motor, kinesthetic, and emotional systems play a role in concept acquisition. These systems support the concepts' cognitive representation in memory, language and thought, thus information contained in them may influence processes associated to word retrieval or word recognition. In the case of the BOI dimension, a facilitatory effect during word recognition is observed because relatively more sensorimotor information is associated with high than low BOI words.

No ERP differences were found between high and low BOI words in the LDT and SCT. It is possible that the N400 is not a sensitive measure for detecting differences in processing between high and low BOI words. Possible generators of the N400 effect include areas such as the superior and middle temporal gyri, the superior temporal sulcus, the anterior temporal medial lobe and the inferior frontal gyrus (Friederici, 2004; Lau et al., 2008). In an fMRI study, Hargreaves et al. (2012) found more activation for high than low BOI words in the supramarginal gyrus, but not in areas thought to generate the N400 effect. Based on current evidence, it is not possible to conclude what are the ERP correlates of BOI, if any, and it is evident that more neuroimaging studies are needed in order to shed light on this issue.

Future studies should aim to implement more powerful neuroimaging techniques such as MEG, or integrate fMRI and EEG to provide a more comprehensive picture of the brain processes taking place.

Chapter 5: General Discussion

This thesis aimed to elucidate the behavioural and ERP correlates of three different semantic richness dimensions as well as their dynamics with task demands. The dimension number of associates (NA) was investigated in the first experiment (chapter 2), while the dimensions number of semantic neighbours (NSN) and body-object interaction (BOI) were investigated in the subsequent experiments (chapters 3 and 4, respectively). To investigate the interaction of each dimension with task demands, I employed two different language task while using the same word stimuli: a LDT and a living/non-living SCT. Comparing the effects in the two tasks allowed me to investigate semantic richness dynamics with task demands because the tasks were presented to the participants in identical manner, the only exception being the decision to be made. While deciding between a real word and a non-word, participants may rely more on familiarity-based information such as word frequency (Balota & Chumbley, 1984) than on semantic variables. In contrast, while deciding whether a word represents a living or non-living entity, participants may rely more on semantic information to make the classification (Yap et al., 2012).

Despite not finding any significant behavioural differences in subject analyses, some semantic richness effects were detected in item analyses. Specifically, high NA words elicited faster and more accurate responses than low NA words. In addition, high BOI words elicited faster responses than low BOI words. These results were significant only in the LDTs. Semantic richness effects were not detected during the living/non-living SCT in any of the dimensions. These results are partially in line with the literature and suggest semantic richness information may not always need to be engaged during language tasks unless it can assist during decision processes.

Importantly, with the ERP technique, I was able to detect semantic richness effects that would not have been detected with simple measures of response time. In agreement with my hypothesis, smaller N400 amplitudes were associated with semantically rich words relative to semantically impoverished words. However, contrary to what I was expecting, these differences were only seen in the NA and NSN dimensions, and only during LDT. N400 effects were not observed for the BOI dimension in either of the tasks, nor in the NA and NSN dimensions during SCT.

These ERP effects may be explained by the knowledge integration hypothesis, which holds that the amplitude of the N400 depends on the amount of knowledge that the brain needs to integrate when processing information (e.g., Hagoort et al., 2009; Rugg, 1990). During LDT, words with high NA and high NSN elicited smaller N400s than low NA and low NSN words, respectively. These results suggest that words with high number of associates or high number of semantic neighbours are processed more efficiently and are easier to integrate than words with few associates or with low number of semantic neighbours, but that this effect depends on the demands of the task. In an LDT, participants have to decide as quickly as they can whether the presented stimulus is a word or not. Thus, the more words associated with or related to a particular target word, the more efficient it is for the brain to make the decision that the presented stimulus is a word. This more efficient processing may be reflected in smaller N400 amplitudes for words with many associates or larger semantic neighbours than words with few associates or smaller semantic neighbours.

On the other hand, the null N400 effect in the living non-living SCT provides evidence that semantic richness is dynamic and can be recruited in a top-down manner depending on task demands. As mentioned previously, some associates or semantic neighbours of high NA and high NSN words may be completely irrelevant or even distracting when trying to make a living/non-living decision (e.g., the associates of the word "duck" include "feather", "rubber", and "pond"). Thus, this knowledge may not be actively recruited in particular contexts, resulting in a null N400 effect. It is possible that during processing of a living/non-living decision task, recruitment of other semantic richness variables such as the number of semantic features may prove more useful. The number of semantic features refers to the properties that belong to a particular concept. These properties are intrinsic to the concept and help define it. Thus, this particular semantic richness variable may be more helpful when making categorical decisions about a concept and may be actively recruited by the brain when necessary, resulting in smaller N400 amplitudes for high than low NoF words when making a living/non-living decision.

This hypothesis is being tested in our lab and results are thus far showing that high NoF words are associated with smaller N400 amplitudes in both the LDT and the living/non-living SCT than low NoF words (Renoult, López Zunini, & Taler, in preparation). This finding suggests that NoF is a useful semantic richness variable in both types of tasks, and supports the results and interpretation of the NA and NSN results. Nevertheless, other hypotheses remain to be tested. For example, future research should investigate whether words that have high number of associates or semantic neighbours that are relevant to a semantic category decision are integrated more quickly than target words with a high number of associates or neighbours that are task-irrelevant.

Given that both NA and NSN are measures of semantic relatedness, albeit operationalized differently, it is perhaps unsurprising to find similar N400 effects. In addition, both measures are considered to be a reflection of semantic memory. However, these effects showed different topographic distributions. One difference between the two measures is that NA is derived from free association experiments where participants are asked to name the first word that comes to mind after a cue word (e.g., the cue word "dog" will likely elicit the word "cat"). In contrast, NSN is captured in a statistical co-occurrence model that examines large corpus of texts. Thus, according to Nelson, McEvoy and Schreiber (2004), while NA measures are a good predictor in cued recall tasks, measures derived from a large corpus of text may be a better predictor of reading comprehension because bodies of text are the basis of such measures. These differences may lead to differing N400 topographies because NA and NSN seem to reflect different aspects of semantic memory.

Another important difference is that free association norms are mostly derived from young adults, whereas the samples used in co-occurrence models can include samples of texts written by adults of all ages. Although semantic memory remains stable during aging (Burke & Mackay, 1997; Luo & Craik, 2008), recent evidence shows that there are age-related differences in the prefrontal-temporal-parietal semantic network (Lacombe, Jolicoeur, Grimault, Pineault, & Joubert, 2015). Thus, aging effects constitute another factor that may explain the differences in topographic maps between the two measures. Although ERP topographic maps can give us an idea of brain activation differences, the spatial resolution of ERP is low. Thus, follow-up studies should aim to replicate the same experiment but with other neuroimaging techniques that have higher spatial resolution, such as MEG or fMRI. This would allow investigation of the similarities and differences in regions of brain activation between the two measures.

In addition, possible additive effects could be investigated by manipulating both measures within one particular task; that is, four different types of stimuli could be investigated: words with both high NA and high NSN, words with high NA and low NSN, words with low NA and high NSN, and words with low NA and low NSN. If the effects are additive, one would expect to find the largest N400 in words with low NA and low NSN, while the smallest N400 would be seen in words that have both high NA and high NSN. Such additive effects would indicate that the variables are measuring different underlying constructs.

Contrary to previous studies, subject analysis did not yield a reaction time advantage for the BOI dimension in lexical decision performance. However, a facilitatory effect was observed in item analyses, indicating that an effect was observed in some participants but not others. In addition, no performance effects were detected in the SCT. Previous studies have shown that high BOI words are recognized faster than low BOI words during SCT. However, these studies employed different categorical decisions, such as concrete/abstract, entity/non-entity or entity/action (Bennett et al., 2011; Tousignant & Pexman, 2012). In contrast, participants in this study had to classify the words as living (which included animals, and plant-life such as fruits and vegetables) or non-living entities. A study investigating the sources of knowledge associated with conceptual categories found that the most relevant source of information for fruits and vegetables was olfactory and gustatory perception, and action (e.g., cutting), whereas for animals, the most relevant source consisted of auditory perception and encyclopedic knowledge (Gainotti, Spinelli, Scaricamazza, & Marra, 2013). This finding seems to be reflected in the words used in the SCT words chosen for the BOI experiment. Many of the living words with high BOI consisted of fruits and vegetables (e.g., strawberry) while many of the living words with low BOI consisted of animals (e.g., lion). It is possible that BOI information –particularly for animals– may not be relevant or may be distracting for this type of decisional category. Thus, explaining the null behavioural effect in the SCT.

Furthermore, the BOI variable did not yield an N400 effect in any of the tasks. The NA and NSN are measures of *semantic relatedness,* whereas BOI quantifies how much sensorimotor information a word possesses. It is possible that the N400 is not sensitive enough to capture BOI effects. According to the fMRI study by Hargreaves et al. (2012), high BOI words elicited more activation in the supramarginal gyrus than low BOI words. High BOI words did not elicit more activation than low BOI words in other regions. Thus, although high BOI words seem to be processed differently than low BOI words, this difference may not be detectable with the N400, which is thought to be generated by several regions, including the superior and middle temporal gyri, the superior temporal sulcus, the anterior medial temporal lobe, and the inferior and the angular gyrus in the inferior parietal lobe (Friederici, 2004; Lau et al., 2008) but not the supramarginal gyrus.

The *flexible lexical processor* framework (Balota & Yap, 2006) states that word recognition is modulated by attentional control directed to appropriate processes (e.g., orthographic, phonological, or semantic) in order to optimally fulfill the requirements of a given language task. Regarding lexical and semantic variables in general, earlier studies provided empirical evidence for this framework by showing that semantic variables are more predictive of lexical decision than of naming performance, while it is primarily word length and phonological information that predict naming performance (Balota et al., 2004; Yap & Balota, 2009). With regards to neural dynamics, a recent meta-analysis of neuroimaging studies showed that lexical decision tasks activate regions associated with semantic processing more than naming tasks (McNorgan, Chabal, O'Young, Lukic, & Booth, 2015). For example, they found that LDTs activated the left middle frontal gyrus and posterior left middle temporal gyrus more than naming tasks; the authors argued that these regions are associated with goal-directed and strategic retrieval of semantic information. In addition, consistent with Balota et al. (2004)'s behavioural evidence, naming was associated with more activation in regions indexing phono-articulatory planning and motor execution relative to lexical decision (McNorgan et al., 2015).

Within the semantic richness literature, much of the empirical evidence supporting the *flexible lexical processor* framework comes from behavioural studies (e.g., Yap et al., 2012; Yap et al., 2011). Behavioural semantic richness studies have demonstrated than the different semantic richness dimensions seem to also be relevant depending upon the demands of the task (Pexman et al., 2008; Yap et al., 2012; Yap et al., 2011). For example, words with many semantic neighbours are recognized faster than words with few neighbours during LDT, while this variable does not have an effect during certain types of SCTs. In contrast, words with a high number of features are recognized faster than words with a low number of features in both LDT and SCT (Pexman et al., 2008; Yap et al., 2012). Similarly, our previous research has shown that words with many senses are recognized faster than words with few senses in LDT (Taler et al., 2013) while an ambiguity disadvantage is observed in SCTs (Hino et al., 2002).

The temporal brain dynamics associated with the interplay between semantic richness and task demands was an area that until this thesis, remained relatively unexplored. This thesis provides neurophysiological evidence that falls within the *flexible lexical processor* framework: different neurophysiological profiles were observed (in the NA and NSN experiments) during performance of two different language tasks, even though word stimuli in both tasks had identical type of information available.

In summary, this thesis investigated the behavioural and ERP correlates of NA, NSN and BOI in two different tasks (LDT vs. SCT). Item analyses revealed than high NA words were associated with more accurate and faster reaction times than low NA words. In addition, high BOI words elicited faster responses than low BOI words. These effects were only detected during LDT, and no behavioural effects were significant in the NSN dimension in any of the tasks. The ERP technique delivered additional information that would have not been captured with simple measures of response time. Results revealed smaller N400 amplitudes for high NA and high NSN than low NA and low NSN words, respectively. These effects were seen during the LDT but not during the SCT. These findings suggest that high NA and NSN words may be integrated more efficiently within the neural network than low NA and low NSN words. However, such semantic richness information may not be always helpful, and may thus be dynamically recruited in a top-down manner depending on task demands, supporting the notion of a *flexible lexical processor*. Finally, no N400 effects were found with the BOI variable, suggesting that the neural correlates of this measure differ from those of NSN and NA (which are thought to reflect semantic relatedness). More studies are needed in order to understand the interplay between NA and NSN, and to elucidate the neural correlates of BOI.

5.1 Limitations

A limitation in these studies is that the ERP technique has poor spatial resolution. Although the ERP technique reflects the activity of a set of neurons with excellent temporal resolution, localizing the precise neural generators is not possible. This is because of the "inverse problem", which states that for any given topographic distribution, there exists an infinite number of possible sets of dipoles that can explain the distribution (Luck, 2005).

An ideal technique for spatial localization is fMRI, which has spatial resolution with millimeter precision. The fMRI technique employs the blood oxygen level dependent (BOLD) response to spatially localize brain activity (Buxton, 2009). When neural activity increases, there is an increase in the demand of oxygen in the regions where the neurons are localized. Increase in the demand of oxygen results in increase in blood flow to that region, where oxygen is carried by hemoglobin molecules in the blood. This hemodynamic response results in a change in the ratio of oxygenated and deoxygenated hemoglobin. Deoxygenated hemoglobin is more magnetic than oxygenated hemoglobin; thus, a change in the ratio of oxygenated vs. deoxygenated hemoglobin is detected by the magnets in the scanner (Buxton, 2009).

As the fMRI technique infers brain activation from the BOLD response, its temporal resolution is on the order of seconds. Thus, the ERP technique, with its high temporal resolution, is an excellent complement for fMRI. With the simultaneous recording of EEG and fMRI, it is possible to elucidate the "where" and "when" of visual word recognition processes. For example, a recent study investigating semantic priming found that the N400 semantic priming effect (i.e., larger N400 for unrelated than related targets) was correlated with activity in the left medial temporal gyrus and the bilateral inferior frontal gyrus (Geukes et al., 2013).

Recall that in this thesis, the N400 effects observed for the NA and NSN dimensions were similar. However, there were scalp distribution differences. Simultaneously recording EEG and fMRI can help shed light on the brain similarities and differences when processing NA and NSN information. Moreover, it can also help understand the null N400 effect observed in the BOI dimension. Perhaps the brain activity associated with processing BOI information is more localized in motor or sensory regions that are not related to the N400 effect. This hypothesis could be tested by comparing both ERP and fMRI activity. Semantic richness effects have yet to be studied with simultaneous recording; thus, this technique has great potential for answering research questions in this area.

5.2 Future directions

Few studies have contrasted semantic richness effects in the visual and auditory modalities. Wurm et al. (2004) found that the variables “danger” and “usefulness” interact to predict reaction time during both visual and auditory word recognition. Recall that the semantic richness variables “danger” and “usefulness” refer to attributes of the objects in the environment that are important for survival. Wurm et al. found that in both the visual and auditory domains words low in usefulness and high in danger elicit faster reaction times, whereas words high in usefulness and high in danger have an inhibitory effect; thus supporting the notion that our experiences in the physical world influence both written and spoken language.

Another study comparing semantic processes in the visual and auditory domain found that words high in imageability were recognized more quickly than words low in imageability in both domains (Armstrong, Barreiro Abad, & Samuel, 2014). However, they found the effect was larger in the auditory than in the visual modality, suggesting that semantic information is processed as a function of sensory modality. This is an area that remains unexplored in cognitive neuroscience, we still do not know how the parallel presentation (written) and the temporally extended (spoken) presentation of a word affect the neural dynamics associated with semantic processing. My future research will explore this question using ERP methodology.

The N400 is a component that is sensitive not only to semantic information but also to orthographic (e.g., orthographic neighbourhood density) and phonologic information (e.g., phonological neighbourhood density) (Grainger et al., 2006; Laszlo & Federmeier, 2012). ERP studies investigating simultaneous effects of orthographic and semantic information have been conducted only in the visual modality. These studies have found that orthographic processes are detectable soon after word onset (within 100-150 ms), and are followed by, and overlap with, processing of semantic information (starting at 200 or 300 ms post-word onset and lasting over 500 ms) (Hauk, Davis, Ford, Pulvermuller, & Marslen-Wilson, 2006; Laszlo & Federmeier, 2014). My future research aims to extend these findings by exploring the interaction of orthographic, phonologic and semantic richness effects in both the visual and auditory domains. By untangling the simultaneous effects of the different types of information associated with a word, my research will aim to establish the relative contribution of orthographic, phonological and semantic information during word meaning extraction –as indexed by the N400– in both sensory domains.

Another area that remains relatively unexplored is the effect of aging on brain mechanisms of word recognition. Behavioural evidence suggests that semantic processing in older adults remains intact. For example, older adults exhibit a reaction time advantage when recognizing words with many associates (Balota et al., 2004; Duñabeitia, Marin, & Carreiras, 2009), or many senses (Taler & Jarema, 2006). However, there is evidence that older adults rely less than young adults on orthographic information such as neighbourhood density when reading words (e.g., Balota et al., 2004), suggesting that some higher-order processes decline while others are well-preserved.

We still do not know why some brain processes associated with word recognition are preserved while others decline during aging. One possibility is that sensory decline may have an effect on higher-order cognitive functions, including word recognition (Burke & Shafto, 2008). During aging, visual and auditory acuity show a steady decline (Burke & Shafto, 2008). According to limited-resource theory, difficulty during sensory processing in older adults would result in fewer cognitive resources available to process higher-order cognitive operations (Burke & Shafto, 2008).

Some studies have found that the N400 component is delayed and reduced in amplitude in older adults relative to young adults (Gunter, Jackson, & Mulder, 1992; Woodward, Ford, & Hammett, 1993), while others have found a reduction in amplitude only (Federmeier, McLennan, De Ochoa, & Kutas, 2002; Federmeier, Van Petten, Schwartz, & Kutas, 2003). Despite these differences, it is not yet clear how access to word meaning and word comprehension –as indexed by the N400 component– is affected by the decline in sensory processing that is typically associated with aging. My future research aims to explore this issue with the ERP technique, which due to its high temporal resolution, is ideal for investigating how very early sensory processes can affect later processes associated with language.

One possibility that can explain why some processes decline while others are preserved, is that older adults allocate more neural resources to early sensory processing than young adults, affecting subsequent orthographic and phonological processes, which can start as early as 100 ms post-stimulus onset (e.g., Hauk et al., 2006). However, later-occurring semantic processes may be protected by compensatory mechanisms. Understanding how and when semantic processes (which can be investigated with semantic richness information associated with words) are affected by normal aging in turn can help us understand the pathological deterioration of the semantic system that is seen in neurodegenerative disorders such as Alzheimer's disease or semantic dementia.

A final future research goal is to integrate findings from the visual and auditory domain comparisons and the effects of aging into a biologically-plausible computational model of word recognition. Using the connectionist approach, Laszlo and Armstrong's computational model of word recognition (2014) could be extended to model orthographic, phonological and semantic processes according to ERP dynamics such as timing of onset, duration and offset, relative order of onset and simultaneity. In addition, neurophysiological activity associated with aging effects could be simulated by synaptic pruning and decreases in connectivity strength. Provided that the model predicts the empirical data, it will be able make predictions about how humans access word meaning. In addition, it may have the potential to offer a mechanistic account of how processes are affected by disorders such as dyslexia, aphasia, or Alzheimer's disease (McClelland & Rogers, 2003). Predictions provided by computational models can in turn generate new hypotheses that can be tested using neuroimaging techniques.

5.3 Conclusions

The goal of the experiments in this thesis was to investigate the dynamics of semantic richness with task demands by systematically comparing effects during two word recognition tasks, and by including the ERP technique to elucidate brain mechanisms. Three different semantic richness dimensions were investigated during lexical decision and semantic categorization tasks: number of associates, number of semantic neighbours and body-object interaction. The results in chapter 2 showed there was a behavioural accuracy and reaction time advantage (in item analyses only) and a smaller N400 for words with high relative to low number of associates during the lexical decision but not during semantic categorization. The results in chapter 3 showed no behavioural differences between high and low NSN items. However, a similar pattern of N400 results as in chapter 2 was seen: smaller N400 for words with high than low number of semantic neighbours, only during lexical decision. Finally, in chapter 4, although a behavioural advantage (in item analyses only) during lexical decision was observed for words with high body-object interaction ratings relative to those with low rating, no N400 differences were detected.

In lexical decision, the smaller N400 amplitudes detected in words with low number of associates or few semantic neighbours relative to words with high number of associates or many semantic neighbours suggest that the brain recognizes words more efficiently when useful information is available. This interpretation is further supported by the null N400 effect observed in semantic categorization performance, because the word stimuli in this task were identical to that of the lexical decision. That is, the same semantic information was available in both tasks. However, such information seemed to only be relevant during LDT.

The null N400 effect in the body-object interaction dimension in both language tasks suggest that either the N400 is not sensitive to the dynamics of this dimension or that the lack of significant results may be related to other factors such as the characteristics of the word list. Clearly, more studies are needed in order to understand this dimension.

This thesis provides evidence that brain processes associated with semantic richness effects are dynamic and support the notion of a *flexible lexical processor* (Balota & Yap, 2006) whereby semantic information may be employed in a top-down manner to fulfill the requirements of the task at hand.

References

Amsel, B. D. (2011). Tracking real-time neural activation of conceptual knowledge using single-trial event-related potentials. *Neuropsychologia, 49*(5), 970-983. doi: 10.1016/j.neuropsychologia.2011.01.003

Amsel, B. D., & Cree, G. S. (2013). Semantic richness, concreteness, and object domain: an electrophysiological study. *Canadian Journal of Experimental Psychology, 67*(2), 117-129. doi: 10.1037/a0029807

Amsel, B. D., Urbach, T. P., & Kutas, M. (2012). Perceptual and motor attribute ratings for 559 object concepts. *Behavior Research Methods, 44*(4), 1028-1041. doi: 10.3758/s13428-012-0215-z

Andrews, S. (1989). Frequency and neighborhood size effects on lexical access: Activation or search? *Journal of Experimental Psychology: Learning, Memory, and Cognition, 15*, 802-814.

Andrews, S., & Heathcote, A. (2001). Distinguishing common and task-specific processes in word identification: a matter of some moment? *Journal of Experimental Psychology. Learning, Memory, and Cognition, 27*(2), 514-544.

Armstrong, B. C., Barreiro Abad, E. , & Samuel, A. G. (2014). *Cascaded semantic access occurs at different rates in spoken versus written word recognition: Evidence from lexical decision*. Paper presented at the Psychonomic Society's 55th Annual Meeting, Long Beach, California, USA.

Balota, D. A. (1990). The role of meaning in word recognition. In D. A. Balota, G. B. Flores d'Arcais & K. Rayner (Eds.), *Comprehension processes in reading* (pp. 9-32). Mahwah, NJ: Lawrence Erlbaum Associates.

Balota, D. A., & Chumbley, J. I. (1984). Are lexical decisions a good measure of lexical access? The role of word frequency in the neglected decision stage. *Journal of Experimental Psychology. Human Perception and Performance, 10*(3), 340-357.

Balota, D. A., Cortese, M. J., Sergent-Marshall, S. D., Spieler, D. H., & Yap, M. J. (2004). Visual word recognition of single-syllable words. *Journal of Experimental Psychology General, 133*(2), 283-316. doi: 10.1037/0096-3445.133.2.283

Balota, D. A., Pilotti, M., & Cortese, M. J. (2001). Subjective frequency estimates for 2,938 monosyllabic words. *Memory and Cognition, 29*(4), 639-647.

Balota, D. A., & Yap, M. J. (2006). Attentional control and flexible lexical processing: exploration of the magic moment of word recognition. In S. Andrews (Ed.), *From inkmarks to ideas: current issues in lexical processing* (pp. 229-258). New York, NY: Psychology Press.

Balota, D. A., Yap, M. J. , Cortese, M. .J. , Hutchison, K. A. , Kessler, B. , Loftis, B. , . . . Treiman, R. (2007). The English Lexicon Project. *Behavior Research Methods, 39*, 445-459.

Barber, H. A., Otten, L. J., Kousta, S. T., & Vigliocco, G. (2013). Concreteness in word processing: ERP and behavioral effects in a lexical decision task. *Brain and Language, 125*(1), 47-53. doi: 10.1016/j.bandl.2013.01.005

Barsalou, L. W. (1999). Perceptual symbol systems. *Behavioral & Brain Sciences, 22*(4), 577-660.

Barsalou, L. W. (2003). Abstraction in perceptual symbol systems. *Philosophical Transactions of the Royal Society of London: Biological Sciences, 358*(1435), 1177-1187. doi: 10.1098/rstb.2003.1319

Barsalou, L. W. (2008). Grounded cognition. *Annual Review of Psychology, 59*, 617-645. doi: 10.1146/annurev.psych.59.103006.093639

Barsalou, L. W., Kyle Simmons, W., Barbey, A. K., & Wilson, C. D. (2003). Grounding conceptual knowledge in modality-specific systems. *Trends in Cognitive Sciences, 7*(2), 84-91. doi: S1364661302000293

Becker, C. A. (1979). Semantic context and word frequency effects in visual word recognition. *Journal of Experimental Psychology. Human Perception and Performance, 5*(2), 252-259.

Bennett, S. D., Burnett, A. N., Siakaluk, P. D., & Pexman, P. M. (2011). Imageability and body-object interaction ratings for 599 multisyllabic nouns. *Behavior Research Methods, 43*(4), 1100-1109. doi: 10.3758/s13428-011-0117-5

Bentin, S., McCarthy, G., & Wood, C. C. (1985). Event-related potentials, lexical decision and semantic priming. *Electroencephalography and Clinical Neurophysiology, 60*(4), 343-355.

Bentin, S., Mouchetant-Rostaing, Y., Giard, M. H., Echallier, J. F., & Pernier, J. (1999). ERP manifestations of processing printed words at different psycholinguistic levels: time course and scalp distribution. *Journal of Cognitive Neuroscience, 11*(3), 235-260.

Besner, D., & Swan, M. (1982). Models of lexical access in visual word recognition. *Quarterly Journal of Experimental Psychology. Human Experimental Psychology, 34*(Pt 2), 313-325.

Borowsky, R. , & Masson, M. E. J. (1996). Semantic ambiguity effects in word identification. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 22*, 63-85.

Braun, M., Jacobs, A. M., Hahne, A., Ricker, B., Hofmann, M., & Hutzler, F. (2006). Model-generated lexical activity predicts graded ERP amplitudes in lexical decision. *Brain Research, 1073-1074*, 431-439. doi: 10.1016/j.brainres.2005.12.078

Brualla, J., Romero, M. F., Serrano, M., & Valdizán, J. R. (1998). Auditory event-related potentials to semantic priming during sleep. *Electroencephalography and Clinical Neurophysiology, 108*(3), 283-290.

Buchanan, L., Westbury, C., & Burgess, C. (2001). Characterizing semantic space: neighborhood effects in word recognition. *Psychonomic Bulletin & Review, 8*(3), 531-544.

Burgess, C., & Lund, K. (2000). Cognitive dynamics: Conceptual and representational change in humans and machines. In E. Dietrich & A. B. Markman (Eds.), *The dynamics of meaning in memory* (pp. 117-156). Mahwah, NJ: Erlbaum.

Burke, D. M., & Mackay, D. G. (1997). Memory, language, and ageing. *Philosophical Transactions of the Royal Society of London., 352*(1363), 1845-1856. doi: 10.1098/rstb.1997.0170

Burke, D. M., & Shafto, M. A. (2008). Language and aging. In F.I.M. Craik & T.A. Salthouse (Eds.), *The handbook of aging and cognition* (pp. 373-444). New York, NY: Psychology Press.

Buxton, R. B. (2009). *Introduction to functional magnetic resonance imaging: Principles and techniques* Cambridge, UK: Cambridge University Press.

Carreiras, M., Duñabeitia, J. A., & Molinaro, N. (2009). Consonants and vowels contribute differently to visual word recognition: ERPs of relative position priming. *Cerebral Cortex, 19*(11), 2659-2670. doi: 10.1093/cercor/bhp019

Carreiras, M., Perea, M., & Grainger, J. (1997). Effects of orthographic neighborhood in visual word recognition: cross-task comparisons. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 23*(4), 857-871.

Chauncey, K., Holcomb, P. J., & Grainger, J. (2008). Effects of stimulus font and size on masked repetition priming: An event-related potentials (ERP) investigation. *Language and Cognitive Processes, 23*(1), 183-200. doi: 10.1080/01690960701579839

Collins, A. M., & Loftus, E. F. (1975). A spreading activation theory of semantic processing. *Psychological Review, 82*, 407-428.

Colombo, L., Pasini, M., & Balota, D. A. (2006). Dissociating the influence of familiarity and meaningfulness from word frequency in naming and lexical decision performance. *Memory and Cognition, 34*(6), 1312-1324.

Coltheart, M. (1981). The MRC Psycholinguistic Database. *Quarterly Journal of Experimental Psychology 33A*, 497-505.

Coltheart, M., Davelaar, E., Jonasson, J., & Besner, D. (1977). Access to the internal lexicon. In S. Dornic (Ed.), *Attention and performance (VI)* (pp. 535-555). Hillsdale, NJ: Erlbaum.

Cortese, M. J., Simpson, G. B., & Woolsey, S. (1997). Effects of association and imageability on phonological mapping. *Psychonomic Bulletin Review, 4*(2), 226-231. doi: 10.3758/BF03209397

Damasio, A. R. (1989). Time-locked multiregional retroactivation: a systems-level proposal for the neural substrates of recall and recognition. *Cognition, 33*(1-2), 25-62. doi: 0010-0277(89)90005-X

Debruille, J. B. (1998). Knowledge inhibition and N400: a study with words that look like common words. *Brain and Language, 62*(2), 202-220. doi: 10.1006/brln.1997.1904

Debruille, J. B. (2007). The N400 potential could index a semantic inhibition. *Brain Research Reviews, 56*(2), 472-477. doi: 10.1016/j.brainresrev.2007.10.001

Debruille, J. B., Ramirez, D., Wolf, Y., Schaefer, A., Nguyen, T. V., Bacon, B. A., . . . Brodeur, M. (2008). Knowledge inhibition and N400: a within- and a between-subjects study with distractor words. *Brain Research, 1187*, 167-183. doi: 10.1016/j.brainres.2007.10.021

Dellantonio, S., Mulatti, C., Pastore, L., & Job, R. (2014). Measuring inconsistencies can lead you forward: Imageability and the x-ception theory. *Frontiers in Psychology, 5*(708). doi: 10.3389/fpsyg.2014.00708

Dufau, S., Grainger, J., & Holcomb, P. J. (2008). An ERP investigation of location invariance in masked repetition priming. *Cognitive, Affective & Behavioral Neuroscience, 8*(2), 222-228.

Dufau, S., Stevens, M., & Grainger, J. (2008). Windows executable software for the progressive demasking task. *Behavior Research Methods, 40*(1), 33-37.

Duñabeitia, J. A., Aviles, A., & Carreiras, M. (2008). NoA's Ark: influence of the number of associates in visual word recognition. *Psychonomic Bulletin & Review, 15*(6), 1072-1077. doi: 10.3758/PBR.15.6.1072

Duñabeitia, J. A., Dimitropoulou, M., Grainger, J., Hernandez, J. A., & Carreiras, M. (2012). Differential sensitivity of letters, numbers, and symbols to character transpositions. *Journal of Cognitive Neuroscience, 24*(7), 1610-1624. doi: 10.1162/jocn_a_00180

Duñabeitia, J. A., Marin, A., & Carreiras, M. (2009). Associative and orthographic neighborhood density effects in normal aging and Alzheimer's disease. *Neuropsychology, 23*(6), 759-764. doi: 10.1037/a0016616

Duñabeitia, J. A., Molinaro, N., Laka, I., Estevez, A., & Carreiras, M. (2009). N250 effects for letter transpositions depend on lexicality: 'casual' or 'causal'? *Neuroreport, 20*(4), 381-387.

Durda, K., & Buchanan, L. (2008). WINDSORS: Windsor improved norms of distance and similarity of representations of semantics. *Behavioral Research Methods, 40*(3), 705-712.

Durda, K., & Buchanan, L. . (2006). WordMine2 [Online] Available. from http://web2.uwindsor.ca/wordmine

Federmeier, K. D., & Laszlo, S. (2009). Time for meaning: Electrophysiology provides insights into the dynamics of representation and processing in semantic memory. In B. Ross (Ed.), *The Psychology of learning and motivation* (Vol. 51, pp. 1-44). Burlington, MA: Academic Press.

Federmeier, K. D., McLennan, D. B., De Ochoa, E., & Kutas, M. (2002). The impact of semantic memory organization and sentence context information on spoken language processing by younger and older adults: an ERP study. *Psychophysiology, 39*(2), 133-146. doi: 10.1017/S0048577202001373

Federmeier, K. D., Van Petten, C., Schwartz, T. J., & Kutas, M. (2003). Sounds, words, sentences: age-related changes across levels of language processing. *Psychology and Aging, 18*(4), 858-872. doi: 10.1037/0882-7974.18.4.858

Ferrand, L., Brysbaert, M., Keuleers, E., New, B., Bonin, P., Meot, A., . . . Pallier, C. (2011). Comparing word processing times in naming, lexical decision, and progressive demasking: evidence from chronolex. *Frontiers in Psychology, 2*, 306. doi: 10.3389/fpsyg.2011.00306

Ferraro, F. R., & Hansen, C. L. (2002). Orthographic neighborhood size, number of word meanings, and number of higher frequency neighbors. *Brain and Language, 82*(2), 200-205.

Fischler, I., Bloom, P. A., Childers, D. G., Roucos, S. E., & Perry, N. W. (1983). Brain potentials related to stages of sentence verification. *Psychophysiology, 20*(4), 400-409.

Fodor, J. A. (1975). *The language of thought*. Cambridge, MA: Harvard University Press.

Forster, K. I. . (1976). Accessing the mental lexicon. In R. J. Wales & E. Walker (Eds.), *New approaches to language mechanisms*. Amsterdam: North-Holland.

Friederici, A. D. (2004). Event-related brain potential studies in language. *Current Neurology and Neuroscience Reports, 4*(6), 466-470.

Friedrich, C. K., Kotz, S. A., Friederici, A. D., & Gunter, T. C. (2004). ERPs reflect lexical identification in word fragment priming. *Journal of Cognitive Neuroscience, 16*(4), 541-552. doi: 10.1162/089892904323057281

Gainotti, G., Spinelli, P., Scaricamazza, E., & Marra, C. (2013). The evaluation of sources of knowledge underlying different conceptual categories. *Frontiers in Human Neuroscience, 7*, 40. doi: 10.3389/fnhum.2013.00040

Ganis, G., & Kutas, M. (2003). An electrophysiological study of scene effects on object identification. *Brain Research. Cognitive Brain Research, 16*(2), 123-144.

Geisser, S. , & Greenhouse, S.W. (1958). An extension of Box's result on the use of F distribution in multivariate analysis. *Annals of Mathematical Statistics, 29*(3), 885-891.

Geukes, S. , Huster, R J. , Wollbrink, A., Jungho, M. , Zwitserlood, P., & Dobel, C. (2013). A large N400 but no BOLD effect – Comparing source activations of semantic priming in simultaneous EEG-fMRI. *PLoS ONE, 8*(12), e84029. doi: 10.1371/journal.pone.0084029

Grainger, J., Kiyonaga, K., & Holcomb, P. J. (2006). The time course of orthographic and phonological code activation. *Psychological Science, 17*(12), 1021-1026. doi: 10.1111/j.1467-9280.2006.01821.x

Gullick, M. M., Mitra, P., & Coch, D. (2013). Imagining the truth and the moon: an electrophysiological study of abstract and concrete word processing. *Psychophysiology, 50*(5), 431-440. doi: 10.1111/psyp.12033

Gunter, T. C., Jackson, J. L., & Mulder, G. (1992). An electrophysiological study of semantic processing in young and middle-aged academics. *Psychophysiology, 29*(1), 38-54.

Hagoort, P., Baggio, G., & Willems, R. M. (2009). Semantic unification. In M. S. Gazzaniga (Ed.), *The cognitive neurosciences* (4th ed., pp. 819-836). Cambridge, MA: MIT Press.

Hagoort, P., Hald, L., Bastiaansen, M., & Petersson, K. M. (2004). Integration of word meaning and world knowledge in language comprehension. *Science, 304*(5669), 438-441. doi: 10.1126/science.1095455

Hargreaves, I. S., Leonard, G. A., Pexman, P. M., Pittman, D. J., Siakaluk, P. D., & Goodyear, B. G. (2012). The neural correlates of the body-object interaction effect in semantic processing. *Frontiers in Human Neuroscience, 6*, 22. doi: 10.3389/fnhum.2012.00022

Hargreaves, I. S., & Pexman, P. M. (2014). Get rich quick: the signal to respond procedure reveals the time course of semantic richness effects during visual word recognition. *Cognition, 131*(2), 216-242. doi: 10.1016/j.cognition.2014.01.001

Hauk, O., Davis, M. H., Ford, M., Pulvermuller, F., & Marslen-Wilson, W. D. (2006). The time course of visual word recognition as revealed by linear regression analysis of ERP data. *Neuroimage, 30*(4), 1383-1400. doi: 10.1016/j.neuroimage.2005.11.048

Heinze, H. J. , Muente, T. F., & Kutas, M. (1998). Context effects in a category verification task as assessed by event-related brain potential (ERP) measures. *Biological Psychology, 47*(2), 121-135.

Hino, Y., Lupker, S. J., & Pexman, P. M. (2002). Ambiguity and synonymy effects in lexical decision, naming, and semantic categorization tasks: interactions between orthography, phonology, and semantics. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 28*(4), 686-713.

Hino, Y., Pexman, P. M. , & Lupker, S. J. (2006). Ambiguity and relatedness effects in semantic tasks: Are they due to semantic coding? . *Journal of Memory and Language* (55), 247-473.

Hoenig, K., Sim, E. J., Bochev, V., Herrnberger, B., & Kiefer, M. (2008). Conceptual flexibility in the human brain: dynamic recruitment of semantic maps from visual, motor, and motion-related areas. *Journal of Cognitive Neuroscience, 20*(10), 1799-1814. doi: 10.1162/jocn.2008.20123

Hoffman, P., Lambon Ralph, M. A., & Rogers, T. T. (2013). Semantic diversity: a measure of semantic ambiguity based on variability in the contextual usage of words. *Behavior Research Methods, 45*(3), 718-730. doi: 10.3758/s13428-012-0278-x

Hoffman, P., & Woollams, A. M. (2015). Opposing effects of semantic diversity in lexical and semantic relatedness decisions. *Journal of Experimental Psychology. Human Perception and Performance, 41*(2), 385-402. doi: 10.1037/a0038995

Holcomb, P. J. (1993). Semantic priming and stimulus degradation: implications for the role of the N400 in language processing. *Psychophysiology, 30*(1), 47-61.

Holcomb, P. J., & Grainger, J. (2006). On the time course of visual word recognition: an event-related potential investigation using masked repetition priming. *Journal of Cognitive Neuroscience, 18*(10), 1631-1643. doi: 10.1162/jocn.2006.18.10.1631

Holcomb, P. J., Grainger, J., & O'Rourke, T. (2002). An electrophysiological study of the effects of orthographic neighborhood size on printed word perception. *Journal of Cognitive Neuroscience, 14*(6), 938-950. doi: 10.1162/089892902760191153

Holcomb, P. J., Kounios, J., Anderson, J. E., & West, W. C. (1999). Dual-coding, context-availability, and concreteness effects in sentence comprehension: an electrophysiological investigation. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 25*(3), 721-742.

Ibáñez, A., López, V., & Cornejo, C. (2006). ERPs and contextual semantic discrimination: degrees of congruence in wakefulness and sleep. *Brain and Language, 98*(3), 264-275. doi: 10.1016/j.bandl.2006.05.005

James, C. T. (1975). The role of semantic information in lexical decisions. *Journal of Experimental Psychology: Human Perception and Performance, 1*, 130-136.

Jastrzembski, J. E. (1981). Multiple meanings, numberof related meanings, frequency of occurrence, and the lexicon. *Cognitive Psychology, 13*, 278-305.

Katz, L. , Brancazio, L. , Irwin, J. , Katz, S. , Magnuson, J., & Whalen, D. H. (2012). What lexical decision and naming tell us about reading. *Reading and Writing, 25*(6), 1259-1282.

Kellas, G., Ferraro, F. R., & Simpson, G. B. (1988). Lexical ambiguity and the timecourse of attentional allocation in word recognition. *Journal of Experimental Psychology. Human Perception and Performance, 14*(4), 601-609.

Kelly, S. D., Kravitz, C., & Hopkins, M. (2004). Neural correlates of bimodal speech and gesture comprehension. *Brain and Language, 89*(1), 253-260. doi: 10.1016/S0093-934X(03)00335-3

Kiefer, M., & Pulvermuller, F. (2012). Conceptual representations in mind and brain: theoretical developments, current evidence and future directions. *Cortex, 48*(7), 805-825. doi: 10.1016/j.cortex.2011.04.006

Klepousniotou, E., & Baum, S. R. (2007). Disambiguating the ambiguity advantage effect in word recognition: An advantage for polysemous but not homonymous words. *Journal of Neurolinguistics, 20*, 1-24.

Klepousniotou, E., Pike, G. B., Steinhauer, K., & Gracco, V. (2012). Not all ambiguous words are created equal: an EEG investigation of homonymy and polysemy. *Brain and Language, 123*(1), 11-21. doi: 10.1016/j.bandl.2012.06.007

Kounios, J., Green, D. L., Payne, L., Fleck, J. I., Grondin, R., & McRae, K. (2009). Semantic richness and the activation of concepts in semantic memory: evidence from event-related potentials. *Brain Research, 1282*, 95-102. doi: 10.1016/j.brainres.2009.05.092

Kounios, J., & Holcomb, P. J. (1994). Concreteness effects in semantic processing: ERP evidence supporting dual-coding theory. *Journal of Experimental Psychology. Learning, Memory and Cognition, 20*(4), 804-823.

Kousta, S. T., Vigliocco, G., Vinson, D. P., Andrews, M., & Del Campo, E. (2011). The representation of abstract words: why emotion matters. *Journal of Experimental Psychology. General, 140*(1), 14-34. doi: 10.1037/a0021446

Kroll, J. F., & Mervis, J. S. (1986). Lexical access for concrete and abstract words. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 12*, 92-107.

Kuperberg, G. R., Sitnikova, T., Caplan, D., & Holcomb, P. J. (2003). Electrophysiological distinctions in processing conceptual relationships within simple sentences. *Brain Research. Cognitive Brain Research, 17*(1), 117-129.

Kutas, M., & Federmeier, K. D. (2000). Electrophysiology reveals semantic memory use in language comprehension. *Trends in Cognitve Sciences, 4*(12), 463-470.

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. doi: 10.1146/annurev.psych.093008.131123

Kutas, M., & Hillyard, S. A. (1980). Reading senseless sentences: brain potentials reflect semantic incongruity. *Science, 207*(4427), 203-205.

Kutas, M., & Hillyard, S. A. (1983). Event-related brain potentials to grammatical errors and semantic anomalies. *Memory and Cognition, 11*(5), 539-550.

Kutas, M., & Hillyard, S. A. (1984). Brain potentials during reading reflect word expectancy and semantic association. *Nature, 307*(5947), 161-163.

Lacombe, J., Jolicoeur, P., Grimault, S., Pineault, J., & Joubert, S. (2015). Neural changes associated with semantic processing in healthy aging despite intact behavioral performance. *Brain and Language, 149*, 118-127. doi: 10.1016/j.bandl.2015.07.003

Laszlo, S., & Armstrong, B. C. (2014). PSPs and ERPs: applying the dynamics of post-synaptic potentials to individual units in simulation of temporally extended Event-Related Potential reading data. *Brain and Language, 132*, 22-27. doi: 10.1016/j.bandl.2014.03.002

Laszlo, S., & Federmeier, K. D. (2012). The N400 as a snapshot of interactive processing: Evidence from regression analyses of orthographic neighbor and lexical associate effects. *Psychophysiology, 48*, 176-186. doi: 10.1111/j.1469-8986.2010.01058.x

Laszlo, S., & Federmeier, K. D. (2014). Never Seem to Find the Time: Evaluating the Physiological Time Course of Visual Word Recognition with Regression Analysis of Single Item ERPs. *Language and Cognitive Processes, 29*(5), 642-661. doi: 10.1080/01690965.2013.866259

Laszlo, S., & Plaut, D. C. (2012). A neurally plausible parallel distributed processing model of event-related potential word reading data. *Brain and Language, 120*(3), 271-281. doi: 10.1016/j.bandl.2011.09.001

Lau, E. F., Phillips, C., & Poeppel, D. (2008). A cortical network for semantics: (de)constructing the N400. *Nature Reviews Neuroscience, 9*(12), 920-933. doi: 10.1038/nrn2532

LeDoux, J. E. (2001). *Synaptic self: How our brains become who we are*. New York, NY: Viking.

Locker, L., Jr., Simpson, G. B., & Yates, M. (2003). Semantic neighborhood effects on the recognition of ambiguous words. *Memory & Cognition, 31*(4), 505-515.

López Zunini, R., Muller-Gass, A., & Campbell, K. (2014). The effects of total sleep deprivation on semantic priming: event-related potential evidence for automatic and controlled processing strategies. *Brain and Cognition, 84*(1), 14-25. doi: 10.1016/j.bandc.2013.08.006

Luck, S. J. (2005). *An introduction to the event-related potential technique*. Cambridge, MA: MIT press.

Lund, K., & Burgess, C. (1996). Producing high-dimensional semantic spaces from lexical co-occurrence. *Behavior Research Methods, Instruments, & Computers, 28*(203-208).

Luo, L., & Craik, F. I. (2008). Aging and memory: a cognitive approach. *Canadian Journal of Psychiatry 53*(6), 346-353.

MacGregor, L. J., Bouwsema, J., & Klepousniotou, E. (2015). Sustained meaning activation for polysemous but not homonymous words: evidence from EEG. *Neuropsychologia, 68*, 126-138. doi: 10.1016/j.neuropsychologia.2015.01.008

Makeig, S., Bell, A. J., Jung, T. P. , & Sejnowski, T. J. (1996). Independent component analysis of electroencephalographic data. In D. Touretzky, M. Mozer & M. Hasselmo (Eds.), *Advances in neural information processing systems* (pp. 145-151).). Cambridge, MA: MIT press.

Maurer, U., Brandeis, D., & McCandliss, B. D. (2005). Fast, visual specialization for reading in English revealed by the topography of the N170 ERP response. *Behavioral and Brain Functions, 1*, 13. doi: 10.1186/1744-9081-1-13

McClelland, J. L., & Rogers, T. T. (2003). The parallel distributed processing approach to semantic cognition. *Nature Reviews Neuroscience, 4*(4), 310-322. doi: 10.1038/nrn1076

McClelland, J. L., & Rumelhart, D. E. (1981). An interactive activation model of context effects in letter perception: part 1. An account of basic findings. *Psychological Review, 88*, 375-407.

McNorgan, C., Chabal, S., O'Young, D., Lukic, S., & Booth, J. R. (2015). Task dependent lexicality effects support interactive models of reading: a meta-analytic neuroimaging review. *Neuropsychologia, 67*, 148-158. doi: 10.1016/j.neuropsychologia.2014.12.014

McRae, K., Cree, G. S., Seidenberg, M. S., & McNorgan, C. (2005). Semantic feature production norms for a large set of living and nonliving things. *Behavior Research Methods, 37*(4), 547-559.

Mirman, D., & Magnuson, J. S. (2008). Attractor dynamics and semantic neighborhood density: processing is slowed by near neighbors and speeded by distant neighbors. *Journal of Experimental Psychology. Learning, Memory and Cognition, 34*(1), 65-79. doi: 10.1037/0278-7393.34.1.65

Monsell, S., Doyle, M. C., & Haggard, P. N. (1989). Effects of frequency on visual word recognition tasks: where are they? *Journal of Experimental Psychology. General, 118*(1), 43-71.

Morton, J. (1969). Interaction of information in word recognition. *Psychological Review, 76*, 165-178.

Morton, J. (1980). The logogen model and orthographic structure. . In U. Frith (Ed.), *Cognitive processes in spelling*. London: Academic Press.

Muller, O., Duñabeitia, J. A., & Carreiras, M. (2010). Orthographic and associative neighborhood density effects: what is shared, what is different? *Psychophysiology, 47*(3), 455-466. doi: 10.1111/j.1469-8986.2009.00960.x

Nelson, D. L., McEvoy, C. L., & Schreiber, T. A. (1990). Encoding context and retrieval conditions as determinants of the effects of natural category size. *Journal of Experimental Psychology. Learning, Memory, and Cognition, 16*(1), 31-41.

Nelson, D. L., McEvoy, C. L., & Schreiber, T. A. (1998). The University of South Florida word association, rhyme, and word fragment norms. from http://www.usf.edu/FreeAssociation/

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.

Nelson, D. L., Schreiber, T. A., & McEvoy, C. L. (1992). Processing implicit and explicit representations. *Psychological Review, 99*(2), 322-348.

New, B., Ferrand, L., Pallier, C., & Brysbaert, M. (2006). Reexamining the word length effect in visual word recognition: new evidence from the English Lexicon Project. *Psychonomic Bulletin and Review, 13*(1), 45-52.

Niedeggen, M., & Roesler, F. . (1999). N400 effects reflect activation spread during retrieval of arithmetic facts. *Psychological Science, 10*(3), 271-276. doi: 10.1111/1467-9280.00149

Osterhout, L. , & Mobley, L. A. (1995). Event-related brain potentials elicited by failure to agree. *Journal of Memory and Language, 34*, 739-773.

Paivio, A., Yuille, J. C., & Madigan, S. A. (1968). Concreteness, imagery, and meaningfulness values for 925 nouns. *Journal of Experimental Psychology, 76*(1), 1-25.

Petit, J. P., Midgley, K. J., Holcomb, P. J., & Grainger, J. (2006). On the time course of letter perception: a masked priming ERP investigation. *Psychonomic Bulletin and Review, 13*(4), 674-681.

Pexman, P. M., Hargreaves, I. S., Edwards, J. D., Henry, L. C., & Goodyear, B. G. (2007). The neural consequences of semantic richness: when more comes to mind, less activation is observed. *Psychological Science, 18*(5), 401-406. doi: 10.1111/j.1467-9280.2007.01913.x

Pexman, P. M., Hargreaves, I. S., Siakaluk, P. D., Bodner, G. E., & Pope, J. (2008). There are many ways to be rich: effects of three measures of semantic richness on visual word recognition. *Psychonomic Bulletin & Review, 15*(1), 161-167.

Pexman, P. M., Lupker, S. J., & Hino, Y. (2002). The impact of feedback semantics in visual word recognition: number-of-features effects in lexical decision and naming tasks. *Psychonomic Bulletin Review, 9*(3), 542-549.

Pexman, P. M., Siakaluk, P. D., & Yap, M. J. (2013). Introduction to the research topic meaning in mind: semantic richness effects in language processing. *Frontiers in Human Neuroscience, 7*, 723. doi: 10.3389/fnhum.2013.00723

Polich, J. (1985). N400s from sentences, semantic categories, number and letter strings? *Bulletin of the Psychonomic Society, 23*(5), 361-364.

Rabovsky, M., Sommer, W., & Abdel Rahman, R. (2012). The time course of semantic richness effects in visual word recognition. *Frontiers in Human Neuroscience, 6*, 11. doi: 10.3389/fnhum.2012.00011

Renoult, L., López Zunini, R. A., & Taler, V. (in preparation). Greater effects of semantic richness in explicit than implicit semantic tasks.

Richardson, J. T. E. (1975). Concreteness and imageability. *Quartely Journal of Experimental Psychology, 27*, 235-249.

Rodd, J. M., Gaskell, G., & Marslen-Wilson, W. D. (2002). Making sense of semantic ambiguity: semantic competition in lexical access. *Journal of Memory and Language, 46*, 245-266. doi: 10.1006/jmla.2001.2810

Rohde, D. L. T., Gonnerman, L. M., & Plaut, D. C. (2005). An Improved Model of Semantic Similarity Based on Lexical Co-Occurrence. from http://www.cnbc.cmu.edu/~plaut/papers/pdf/RohdeGonnermanPlautSUB-CogSci.COALS.pdf

Rolke, B., Heil, M., Streb, J., & Hennighausen, E. (2001). Missed prime words within the attentional blink evoke an N400 semantic priming effect. *Psychophysiology, 38*(2), 165-174.

Rugg, M. D. (1985). The effects of semantic priming and word repetition on event-related potentials. *Psychophysiology, 22*, 642-647.

Rugg, M. D. (1990). Event-related brain potentials dissociate repetition effects of high- and low-frequency words. *Memory and Cognition, 18*(4), 367-379.

Rugg, M. D., Furda, J., & Lorist, M. (1988). The effects of task on the modulation of event-related potentials by word repetition. *Psychophysiology, 25*, 55-63.

Sears, C. R., Lupker, S. J., & Hino, Y. (1999). Orthographic neighborhood effects in perceptual identification and semantic categorization tasks: a test of the multiple read-out model. *Perception & Psychophysics, 61*(8), 1537-1154.

Seidenberg, M. S., & McClelland, J. L. (1989). A distributed, developmental model of word recognition and naming. *Psychological Review, 96*(4), 523-568.

Senkowski, D., Schneider, T. R., Foxe, J. J., & Engel, A. K. (2008). Crossmodal binding through neural coherence: implications for multisensory processing. *Trends in Neurosciences, 31*(8), 401-409. doi: 10.1016/j.tins.2008.05.002

Shaoul, C., & Westbury, C. (2010). Exploring lexical co-occurrence space using HiDEx. *Behavior Research Methods, 42*(2), 393-413. doi: 10.3758/BRM.42.2.393

Siakaluk, P. D., Buchanan, L., & Westbury, C. (2003). The effect of semantic distance in yes/no and go/no-go semantic categorization tasks. *Memory & Cognition, 31*(1), 100-113.

Siakaluk, P. D., Pexman, P. M., Aguilera, L., Owen, W. J., & Sears, C. R. (2008). Evidence for the activation of sensorimotor information during visual word recognition: the body-object interaction effect. *Cognition, 106*(1), 433-443. doi: 10.1016/j.cognition.2006.12.011

Siakaluk, P. D., Pexman, P. M., Sears, C. R., Wilson, K., Locheed, K., & Owen, W. J. (2008). The benefits of sensorimotor knowledge: body-object interaction facilitates semantic processing. *Cognitive Science, 32*(3), 591-605. doi: 10.1080/03640210802035399

Sitnikova, T., Holcomb, P. J., Kiyonaga, K. A., & Kuperberg, G. R. (2008). Two neurocognitive mechanisms of semantic integration during the comprehension of visual real-world events. *Journal of Cognitive Neuroscience, 20*(11), 2037-2057. doi: 10.1162/jocn.2008.20143

Strain, E., Patterson, K., & Seidenberg, M. S. (1995). Semantic effects in single-word naming. *Journal of Experimental Psychology. Learning, Memory and Cognition, 21*(5), 1140-1154.

Stuss, D. T., Picton, T. W., & Cerri, A. M. (1988). Electrophysiological manifestations of typicality judgment. *Brain and Language, 33*(2), 260-272.

Swaab, T. Y., Baynes, K., & Knight, R. T. (2002). Separable effects of priming and imageability on word processing: an ERP study. *Brain Research. Cognitive Brain Research, 15*(1), 99-103. doi: S0926641002002197

Taler, V., & Jarema, G. (2006). On-line lexical processing in AD and MCI: An early measure of cognitive impairment? *Journal of Neurolinguistics, 19* 38-55.

Taler, V., Kousaie, S., & López Zunini, R. (2013). ERP measures of semantic richness: the case of multiple senses. *Frontiers in Human Neuroscience, 7*, 5. doi: 10.3389/fnhum.2013.00005

Taler, V., & Phillips, N. A. (2007). Event-related brain potential evidence for early effects of neighborhood density in word recognition. *Neuroreport, 18*(18), 1957-1961. doi: 10.1097/WNR.0b013e3282f202f5

Tillotson, S. M., Siakaluk, P. D., & Pexman, P. M. (2008). Body-object interaction ratings for 1,618 monosyllabic nouns. *Behavior Research Methods, 40*(4), 1075-1078. doi: 10.3758/BRM.40.4.1075

Tolentino, L. C. , & Tokowicz, N. (2009). Are pumpkins better than heaven? An ERP investigation of order effects in the concrete-word advantage. *Brain and Language, 110*, 12-22.

Tousignant, C., & Pexman, P. M. (2012). Flexible recruitment of semantic richness: context modulates body-object interaction effects in lexical-semantic processing. *Frontiers in Human Neuroscience, 6*, 53. doi: 10.3389/fnhum.2012.00053

Van Berkum, J. J., van den Brink, D., Tesink, C. M., Kos, M., & Hagoort, P. (2008). The neural integration of speaker and message. *Journal of Cognitive Neuroscience, 20*(4), 580-591. doi: 10.1162/jocn.2008.20054

Vergara-Martinez, M., Perea, M., Gomez, P., & Swaab, T. Y. (2013). ERP correlates of letter identity and letter position are modulated by lexical frequency. *Brain and Language, 125*(1), 11-27. doi: 10.1016/j.bandl.2012.12.009

Welcome, S. E., Paivio, A., McRae, K., & Joanisse, M. F. (2011). An electrophysiological study of task demands on concreteness effects: evidence for dual coding theory. *Experimental Brain Research, 212*(3), 347-358. doi: 10.1007/s00221-011-2734-8

Wellsby, M., Siakaluk, P. D., Owen, W. J., & Pexman, P. M. . (2011). Embodied semantic processing: The body-object interaction effect in a non-manual task. *Language & Cognition, 3*, 1-14.

West, W. C., & Holcomb, P. J. (2000). Imaginal, semantic, and surface-level processing of concrete and abstract words: an electrophysiological investigation. *Journal of Cognitive Neuroscience, 12*(6), 1024-1037.

Whaley, C. P. (1978). Word non-word classification time. *Journal of Verbal Learning and Verbal Behavior, 17*, 143-154.

Woodward, S. H., Ford, J. M., & Hammett, S. C. (1993). N4 to spoken sentences in young and older subjects. *Electroencephalography and Clinical Neurophysiology, 87*(5), 306-320.

Wurm, L. H., & Vakoch, D. A. (2000). The adaptive value of lexical connotation in speech perception. *Cognition and Emotion, 14*, 177-191.

Wurm, L. H., Vakoch, D. A., Seaman, S. R., & Buchanan, L. (2004). Semantic effects in auditory word recognition. *Mental Lexicon Working Papers, 1*, 47-62.

Yap, M. J., & Balota, D. A. (2007). Additive and interactive effects on response time distributions in visual word recognition. *Journal of Experimental Psychology. Learning, Memory and Cognition, 33*(2), 274-296. doi: 10.1037/0278-7393.33.2.274

Yap, M. J., & Balota, D. A. (2009). Visual word recognition of multisyllabic words. *Journal of Memory and Language, 60*, 502-529. doi: 10.1016/j.jml.2009.02.001

Yap, M. J., & Balota, D. A. (2015). Visual word recognition. In A. Pollatsek & R. Treiman (Eds.), *The Oxford handbook of reading*. (pp. 26-43). New York, NY: Oxford University Press.

Yap, M. J., Pexman, P. M., Wellsby, M., Hargreaves, I. S., & Huff, M. J. (2012). An abundance of riches: cross-task comparisons of semantic richness effects in visual word recognition. *Frontiers in Human Neuroscience, 6*, 72. doi: 10.3389/fnhum.2012.00072

Yap, M. J., Tan, S. E., Pexman, P. M., & Hargreaves, I. S. (2011). Is more always better? Effects of semantic richness on lexical decision, speeded pronunciation, and semantic classification. *Psychonomic Bulletin & Review, 18*(4), 742-750. doi: 10.3758/s13423-011-0092-y

Yates, M., Locker, L., Jr., & Simpson, G. B. (2003). Semantic and phonological influences on the processing of words and pseudohomophones. *Memory & Cognition, 31*(6), 856-866.

Appendix A

List of words for the NA experiment

High NA, living	Low NA, living	High NA, non-living	Low NA, non-living
rodent	beetle	cracker	chamber
oyster	cod	deodorant	drill
vegetable	crow	gown	encyclopedia
bunny	hare	barn	office
cattle	pony	jewel	rail
insect	cub	lid	cable
nut	buffalo	pancakes	bolt
snake	flea	flute	keys
bear	gopher	weapon	museum
mammal	hawk	poison	poster
fruit	hornet	cord	supper
bug	swan	loan	café
cow	toad	hamburger	stool
shark	tortoise	spice	shed
baby	mare	ticket	juice
bird	sage	sink	zipper
bee	plum	bowl	emerald
duck	berry	chain	pedal
worm	parrot	garbage	telescope
kitten	pigeon	block	linen
fox	cricket	clay	van
puppy	koala	fork	village
seal	primate	whip	mattress
dove	fig	hook	sleeve
goose	moth	hose	jeep
ant	physician	cage	cork
squash	mice	robe	kite
peach	citizen	dough	pier
crab	maple	thorn	sack
wolf	daisy	mall	drapes

Appendix B

List of words for the NSN experiment

High NSN, living	Low NSN, living	High NSN, non-living	Low NSN, non-living
celery	shrimp	sofa	airplane
chicken	apple	bench	ambulance
pine	leaf	cabinet	colander
broccoli	pineapple	dress	balloon
corn	vine	jeans	bag
onions	turkey	cottage	letter
parsley	hen	couch	sand
pepper	rat	stone	canoe
tomato	fish	sweater	hat
beets	frog	vest	envelope
grass	lime	yolk	hammer
lettuce	mandarin	cake	trombone
oak	moose	chair	kettle
owl	guy	lamp	bus
sheep	ape	pipe	clarinet
spinach	bean	shoes	lantern
cabbage	pear	socks	pencil
cat	bouquet	veil	pin
cauliflower	plant	violin	pillow
elk	cherry	bed	anchor
dog	trout	bottle	pearl
garlic	walnut	bridge	blanket
horse	whale	church	cookie
lemon	radish	coat	paper
olive	groom	bread	harp
nightingale	camel	jacket	pliers
peas	coconut	pistol	saxophone
tree	lamb	trousers	pie
geese	cranberry	boots	drum
flower	grape	mug	crowbar

Appendix C

List of words for the BOI experiment

High BOI, living	Low BOI, living	High BOI, non-living	Low BOI, non-living
rhubarb	dinosaur	yacht	ace
pet	tiger	blouse	rocket
pumpkin	gorilla	saddle	city
orange	elephant	apron	chimney
mate	squirrel	bracelet	closet
raspberry	lizard	elevator	chandelier
tangerine	rabbit	needle	sewer
oat	mosquito	axe	manor
tulip	prairie	scissors	mansion
seed	waiter	cigarette	rectangle
kid	finch	camera	igloo
mushroom	sailor	thermometer	submarine
nurse	donkey	telephone	antlers
mule	dolphin	wallet	statue
garden	lion	razor	corridor
peanut	meadow	wagon	station
nutmeg	pinecone	chalk	orchestra
grapefruit	peacock	ladder	tunnel
eggplant	pirate	cushion	basement
seaweed	raccoon	revolver	missile
cucumber	panda	diaper	dam
bride	walrus	mallet	bungalow
potato	lobster	helmet	helicopter
strawberry	kangaroo	pajamas	alley
lawn	hippopotamus	tricycle	propeller
wheat	alligator	bucket	medal
banana	eagle	umbrella	balcony
carrot	turtle	steak	platform
orchard	spider	ribbon	suburb
watermelon	leopard	trumpet	cannon

Appendix D

López Zunini, R. A., Muller-Gass, A., & Campbell, K. (2014). The effects of total sleep deprivation on semantic priming: event-related potential evidence for automatic and controlled processing strategies. Brain and Cognition, 84(1), 14-25.

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The effects of total sleep deprivation on semantic priming: Event-related potential evidence for automatic and controlled processing strategies

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ABSTRACT

There is general consensus that performance on a number of cognitive tasks deteriorates following total sleep deprivation. At times, however, subjects manage to maintain performance. This may be because of an ability to switch cognitive strategies including the exertion of compensatory effort. The present study examines the effects of total sleep deprivation on a semantic word priming task. Word priming is unique because it can be carried out using different strategies involving either automatic, effortless or controlled, effortful processing. Twelve subjects were presented with word pairs, a prime and a target, that were either highly semantically associated (*cat*...*dog*), weakly associated (*cow*...*barn*) or unassociated (*apple*...*road*). In order to increase the probability of the use of controlled processing following normal sleep, the subject's task was to determine if the target word was semantically related to the prime. Furthermore, the time between the offset of the prime and the onset of the target was relatively long, permitting the use of an effortful, expectancy-predictive strategy. Event-related potentials (ERPs) were recorded from 64 electrode sites. After normal sleep, RTs were faster and accuracy higher to highly associated targets; this performance advantage was also maintained following sleep deprivation. A large negative deflection, the N400, was larger to weakly associated and unassociated targets in both sleep-deprived and normal conditions. The overall N400 was however larger in the normal sleep condition. Moreover, a long-lasting negative slow wave developed between the offset of the prime and the onset of the target. These physiological measures are consistent with the use of an effortful, predictive strategy following normal sleep but an automatic, effortless strategy following total sleep deprivation. A picture priming task was also run. This task benefits less from the use of a predictive strategy. Accordingly, in this task, ERPs following the target did not differ as a function of the amount of sleep.

1. Introduction

Total sleep deprivation affects performance on several different cognitive tasks. The detriment in performance often appears as a slowing of reaction time (RT) or as a decrease in the accuracy of detection. Not all studies however report this detriment in performance, often suggesting that the maintenance of performance might be a result of a change of cognitive strategy in order to "compensate" for the effects of sleep deprivation (Lim & Dinges, 2008). In many instances, such compensation involves a strategy of increasing "effort". The present study is unusual in that it employs a semantic priming paradigm, a task in which performance can be successfully carried out using different cognitive strategies. The semantic priming task can be carried out using active, effortful processing, requiring therefore the maintenance of sustained attention. It can also however be carried out using effortless, automatic processing and thus does not require the maintenance of sustained attention. The former strategy might be appropriate when cognitive resources are readily available, following normal sleep. The latter might be appropriate when fewer cognitive resources are available, following sleep deprivation.

In word priming tasks, the subject is presented with an initial word (the "prime") that may or may not be semantically associated with a subsequent "target" word. There are several variants of the paradigm but often the subject is engaged in an incidental lexical decision task, having to determine if the target word is a valid word or not. When the prime is semantically associated with the target (e.g., *cat*...*dog*), RTs are faster and accuracy higher than when the prime is not associated with the target (e.g., *doctor*...*mouse*). This is referred to as the "priming effect". A common theory to explain the priming advantage proposes a spreading activation across a semantic memory network with strongly associated semantic concepts represented in neighbouring nodes and weakly associated

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concepts represented in more distant nodes. Thus, target words that are strongly semantically associated with the prime are activated rapidly and are therefore available to memory prior to the onset of the target. Targets that are only weakly associated with the prime are activated more slowly because of their representation in more distant nodes. Targets that are not associated with the prime cannot be retrieved within the semantic network and are thus not available to memory prior to the onset of the target (Collins & Loftus, 1975; Neely, 1991).

The search of the semantic network can be carried out using either automatic, effortless or controlled, effortful processing. Collins and Loftus (1975) initially claimed that the spreading activation across the semantic network occurred automatically, without the need for attention or effort. Support for this claim comes from priming studies in which the subject is asked to make a lexical decision about the target. The semantic association between the prime and the target is thus irrelevant to the lexical decision task. Even though attention is not directed to the nature of the semantic association between the prime-target word pair, and the subject may not be aware of their association, a strong priming effect still, seemingly automatically, occurs. Other authors indicate that even though attention might not be directed to the semantic association between the prime and the target, after a few trials, the subject may well become aware of the association. The subject might thus use an alternative, predictive expectancy-based strategy (Becker, 1980; Neely, 1976; Posner & Snyder, 1975). Subjects can therefore use the prime to intentionally generate an expectancy for a set of semantically associated target candidates. The set of expected targets for the prime *dog* might include *cat*, *poodle*, *bark*, *tail* and so forth. For this reason, expectancy-based strategies are effective only at longer stimulus onset asynchronies (SOAs), when the time interval between the onset of the prime and that of the target is sufficiently long to allow subjects to generate possible exemplars (den Heyer, Briand, & Dannenbring, 1983; Neely, 1976). The expectancy-based strategy does come at a cost – it does require active and sustained attention in order to search out possible target exemplar candidates and maintain them in working memory.

The effects of sleep deprivation on priming have not been studied extensively. Swann, Yelland, Redman, and Rajaratnam (2006) employed a repetition priming task following normal sleep and following two consecutive nights of restricted sleep (40% less than normal sleep). Subjects were presented with a brief duration 56 ms initial prime word and at its offset, a 500 ms target. The target was either a real word or a non-word and subjects were asked to button press if a real word had been presented. Two different prime-target pairs were employed. The identical (ID) prime was the same word as the target (e.g. *blue-blue*), and the all letters different (ALD) prime had letters that were different at each position in the letter string compared to the target (e.g. *sand-blue*). Following normal sleep, regardless of whether the target was a real word or not, RTs were faster in the ID condition, when the target matched the prime than in the ALD condition, when the target did not match the prime. Because the initial prime was masked and the subject could not consciously identify it, the faster RTs in the ID condition were explained by an automatic, nonconscious activation of lexical (or possibly sensory) memory prior to the onset of the target. Of course, the lexical memory for the ALD targets could not have been activated upon presentation of the prime. Interestingly, RTs were faster for the ID targets following sleep deprivation compared to normal sleep indicating that the automatic processing of the target was preserved, but were slower for the ALD targets. Thus, the overall repetition priming effect was enhanced by sleep deprivation. Swann et al. (2006) suggested that this might be because of the use of compensatory effort, possibly involving the recruitment of additional cognitive resources. Importantly, repetition priming does not access the strength of semantic association networks. Nevertheless, the results of this study do endorse the notion that tasks that only require automatic, effortless processing, such as those involved in the access of the lexical network, are well-preserved following sleep deprivation.

A problem with studies that rely strictly on performance measures, such as RT and accuracy, is that conclusions about information processing strategies must be inferred and cannot directly be observed. In semantic word priming tasks, as noted, it is possible for subjects to employ at least two different strategies (involving either automatic or controlled processing). Depending on the availability of attentional resources, subjects may favour one strategy over another. It is thus possible that the behavioural performance of the subjects who are sleep-deprived will not differ from those who have slept normally. A failure to find a difference in performance cannot be used as evidence of a similarity of cognitive strategies. Many laboratories therefore employ physiological measures, such as event-related potentials (ERPs), to measure cognitive processes prior to, at the time of, and following a behavioural decision. ERPs are the minute changes in the electrical activity of the brain that are elicited by an external physical, sensory stimulus or an internal, cognitive event. ERPs consist of a series of negative- and positive-going components thought to reflect different stages of information processing. In the study of semantic priming, ERPs can be recorded during the entire interval from the time of presentation of the prime and continue for a period of time after the presentation of the target, providing an elegant means to monitor the use of different cognitive strategies.

A number of studies have investigated the effects of sleep deprivation on many different ERP components. Most of these studies have however recorded ERPs during tasks that require active, sustained vigilance. For example, a negative deflection peaking at about 150–200 ms associated with sustained attention to a visual stimulus has been shown to be reduced in amplitude following sleep deprivation (Hoedlmoser et al., 2011; Smith, McEvoy, & Gevins, 2002; Trujillo, Kornguth, & Schnyer, 2009). Similarly, a later positive component, P300 (also labelled as P3b), associated with the detection of a rare target stimulus during vigilance tasks has also been shown to be attenuated following sleep deprivation (Corsi-Cabrera, Arce, Del Rio-Portilla, Perez-Garci, & Guevara, 1999; Gosselin, De Koninck, & Campbell, 2005; Morris, So, Lee, Lash, & Becker, 1992; Smith et al., 2002). Subjects often make more errors following sleep deprivation. An error-related negativity (ERN), thought to be related to error detection or response conflict, and a subsequent positivity (Pe), related perhaps to the actual error recognition may also be attenuated by sleep deprivation (Hsieh, Tsai, & Tsai, 2009; Murphy, Richard, Masaki, & Segalowitz, 2006; Scheffers, Humphrey, Stanny, Kramer, & Coles, 1999).

An ERP component that is consistently modulated by manipulations of semantic context is the N400, a negative-going waveform peaking at about 400 ms. In semantic studies, the amplitude of the N400 is large when the target stimulus is presented without any context. It is attenuated (less negative) when a target word is preceded by a semantically congruent context (Kutas & Federmeier, 2011). Thus in word priming tasks, N400 is large to targets that are semantically unassociated with the prime or only weakly associated with it and small to targets that are strongly associated with the prime (Bentin, McCarthy, & Wood, 1985; Chwilla & Kolk, 2005; Holcomb, 1988; Phillips, Segalowitz, O'Brien, & Yamasaki, 2004). The effects are similar across different modalities such as picture–word naming and association tasks (Blackford, Holcomb, Grainger, & Kuperberg, 2012; Hurley et al., 2009; Khateb, Pegna, Landis, Mouthon, & Annoni, 2010). Importantly, the N400 can be elicited whether subjects use an automatic or a controlled expectancy-based strategy (Deacon, Uhm, Ritter, Hewitt, & Dynowska, 1999). The present study was designed to optimise the probability that subjects would use an expectancy-based predictive strategy following normal sleep. To do so, the subject's attention was intentionally directed to the nature of the semantic association between the prime and the target. The task was thus to determine whether the target was semantically associated with the preceding prime. This also has the advantage that the N400 effect is larger when attention is directed to the semantic association between the prime and target (Holcomb, 1988). In addition, the time between the onset of the prime and the subsequent target was 700 ms, long enough to permit the use of an expectancy-based cognitive strategy. It was unlikely that the sustained attention required for the expectancy-predictive strategy could be maintained following total sleep deprivation. The alternative, automatic strategy, could however be employed to assure successful performance.

The controlled, predictive strategy is not effective in all semantic priming tasks. In picture association tasks, a subject might be presented with an image of an object followed by a word that may or may not name it. The picture–word priming association task is less susceptible to strategic, predictive processing (Huttenlocher & Kubicek, 1983; Keefe & Neely, 1990). Therefore, in a second condition, a picture–word association task was used. Subjects were presented with a picture and a subsequent target word that either named the picture, was weakly associated with it or was not associated with it. The subject's task was again to determine if the target word was semantically associated with the picture. However, to do so, the subject does need to initially generate the name of the picture, a complex cognitive process. In this case, even with a 700 ms SOA, there would likely be insufficient time to also predict semantic associates prior to the onset of the target word.

2. Methods

2.1. Subjects

Twelve young adults (6 males, 6 females) from 20 to 31 years of age (Mean = 24.3; SD = 3.7 years) volunteered to participate in this study. All were right-handed, with good self-reported health, normal or corrected-to-normal eyesight and were not taking any medications known to affect cognitive function. None had a history of neurological or psychiatric disorder. Absence of sleep disorders was verified using the Pittsburgh Sleep Index (Buysse, Reynolds, Monk, Berman, & Kupfer, 1989). Subjects were required to maintain a regular sleep schedule (no night or shift work) and to abstain from alcohol and caffeine in the 24 h period prior to the start of data collection. This study was conducted following the guidelines of the Canadian Tri-Council (Health, Natural, and Social Sciences) on ethical conduct involving humans. All subjects gave written informed consent prior to the beginning of the experiment and were paid an honorarium for their participation.

2.2. Procedure

All subjects participated in two experimental sessions: one following a normal night of sleep, and one following total sleep deprivation. The order of the sessions was counterbalanced across participants and at least one week separated the two sleep conditions. Thus, subjects had ample time to recover from the effects of sleep deprivation.

Subjects were asked to retire for sleep and to awaken at the same times for four consecutive nights prior to both the normal sleep and sleep deprivation sessions. They completed sleep logs each morning upon awakening. The sleep patterns did not differ prior to the normal sleep and sleep deprivation sessions. On the sleep-deprived night, a research assistant was present at all times to ensure subjects did not sleep even for brief periods of time. Subjects watched videos, read or played computer games for the entire duration of the night. The data collection occurred between 10:00 and 13:00. Upon coming to the lab, subjects completed the Stanford Sleepiness Scale, a 9-point rating scale (1 = awake and alert, 8 = falling asleep, 9 = asleep).

2.3. Experimental tasks

Subjects engaged in a word association task and a picture–word association task during the two sleep conditions. Half the subjects performed the word association task first and the other half, the picture–word association task on their initial visit to the lab. The order of presentation was reversed on the second visit to the lab.

Stimulus presentation and response monitoring were controlled by E-prime software (Psychology Software Tools Inc., Sharpsburg, Pennsylvania) using a PC with a Windows XP operating system. Subjects sat about 0.6 m at eye height in front of an LCD monitor. For both the word- and picture–word association tasks, each trial started with a fixation point ("+") presented in the centre of a monitor for 2000 ms. Next, the prime (either a word or a picture in different conditions) was presented for 200 ms followed by a 500 ms inter-stimulus interval. A target word was then presented for a maximum of 1200 ms or until the participant made a response.

2.3.1. Word association task

Three different target types were presented: Strongly associated (e.g., *dog-cat*), Weakly associated (e.g., *cow-barn*) and Unassociated (e.g., *apple-road*). The subject was asked to press one mouse button if the target was semantically associated with the prime and a different button if the target was not associated with the prime. Thus, the same response button was to be used for the strongly and weakly associated targets. All words were presented in lower case and subtended a horizontal visual angle between 3° and 12° and a vertical angle of 1°. The Edinburgh Associative Thesaurus (Kiss, Armstrong, Milroy, & Piper, 1973) was used to establish the strength of the prime-target association. The extent of association for Strong prime-targets exceeded 0.60 (Mean = 0.68, SD = 0.10) and for Weak prime-targets did not exceed 0.10 (Mean = 0.09, SD = 0.01). There was no semantic association for the unassociated prime and target words.

A total of 420 prime-target pairs were constructed and were randomly divided into two lists that included 70 pairs of each of the prime-target association types. The strength of association between the prime and the target did not significantly differ between the two lists. Subjects were presented with both lists, one during each experimental session. Subjects did not therefore see the same prime-target pairs more than once. Half the subjects were presented with one list initially and the other half, with the second list.

2.3.2. Picture association task

Three different target types were presented: Named (e.g., picture of a hand followed by the word *hand*), Weakly associated (e.g., picture of a guitar followed by the word *piano*) or Unassociated (e.g., picture of a cow followed by the word *planet*). Again, subjects were asked to click one mouse button if the target either named or was associated with the prime and a different mouse button if the target was not associated with the prime. Pictures were all concrete objects (and thus easily named) downloaded from the International Picture Naming database (http://crl.ucsd.edu/experiments/ipnp/1references.html). Norms for picture naming are also available in this database. The pictures were presented on a light grey background and subtended a horizontal and vertical angle both varying between 10° and 18°. The words were again presented in lower case.

A total of 420 picture–words pairs were constructed and again divided at random into two lists, each list thus containing 70 prime-target pairs for each of the 3 target types. The percentage of naming agreement in the normative database was 89% for the 420 pictures. The naming agreement did not significantly differ between the two lists. Further, the naming agreement of pictures did not significantly vary as a function of the type of target word that followed. In the case of the target words that did not name the pictures but were associated with it, the mean strength of association according to the Edinburgh Association Thesaurus was 0.10 (SD = 0.10). There was no semantic association between the unassociated prime and target words.

2.3.3. ERP recording

EEG activity was recorded from 63 sites over frontal, central, parietal, temporal and occipital sites using active silver-silver chloride electrodes attached to an electrode cap (Brain Products, GmbH, Munich, Germany). An EOG electrode was placed on the infra-orbital ridge of the left eye to record vertical eye movements. The nose was used as a reference for all channels.

Inter-electrode impedances varied from 20 to 50 kΩ. A high filter was set at 500 Hz. The time constant was 2 s. The EEG was continuously digitized at a 500 Hz sampling rate and stored on hard disc for later analyses. Offline, the data were reconstructed using Brain Products' Analyzer2 software. Vertical EOG activity was computed by subtracting data recorded at FP1 from that at the lower EOG site. Horizontal EOG activity was computed by subtracting data recorded at FT9 from that recorded at FT10.

The continuous data were digitally filtered using a high filter set at 20 Hz. The EEG was visually inspected for channels containing high levels of noise. These channels were replaced by interpolating the data of the surrounding electrode sites (Perrin, Pernier, Bertrand, & Echallier, 1989). Independent Component Analysis (Makeig, Bell, Jung, & Sejnowski, 1996) was used to identify eye movements and blinks that were statistically independent of the EEG activity. This algorithm was trained to recognise each subject's blink signature, and this factor was then partialled out of the EEG traces.

2.4. Data analyses

2.4.1. Behavioural performance

Performance was measured in terms of accuracy (hit rate) and RT. Subjects were instructed to respond while the stimulus was still displayed (i.e., within 1200 ms). Outlier RTs longer than 1200 ms were removed from the analysis. In the sleep deprivation condition, two subjects failed to achieve an accuracy rate above chance level (two-thirds of the targets were associated with the prime while one-third were not) during the word association task. These subjects were therefore rejected from further analysis of the performance and physiological data in both the sleep deprivation and normal sleep conditions. During the picture association task, one subject failed to attain chance accuracy and was therefore again rejected from further analysis. This subject also failed to attain chance accuracy on the word association task. A 2-way ANOVA with repeated measures on target association (3 levels; strongly associated in the case of the word association task or named in the case of the picture association task, weakly associated and unassociated) and sleep condition (2 levels: sleep deprivation, normal sleep) was carried on the dependent measures. Separate ANOVAs were run on the word and picture association task data.

2.4.2. ERP data

The continuous EEG was reconstructed into discrete 2000 ms epochs starting 100 ms before the onset of the prime (word or picture). The epoch thus contained ERPs elicited by both the prime and the subsequent target.

Two epochs were subsequently defined, one for the ERPs elicited by the prime stimulus and a second for the ERPs elicited by the target words. Single epochs were sorted and averaged according to electrode position and prime-target association strength. Only correct trials were averaged. ERP peaks deflections are often quantified relative to a pre-stimulus baseline. This was appropriate for the quantification of the prime word and picture stimuli. However, as discussed below, the pre-target period proved to be different in the normal sleep and sleep deprivation conditions. The prime epoch began 100 ms prior to onset of the stimulus and continued for another 800 ms following it. The single trial epochs were then baseline corrected prior to averaging. Any epochs containing EEG activity exceeding ±100 μV on any channel were rejected from averaging. The prime word waveform consisted of a central maximum positive deflection at about 200 ms followed by a negativity at about 300 ms. The P200 was quantified by averaging all data points within ±30 ms of the peak identified in the grand average. The early processing of the pictures differed from that of the words. The picture waveform consisted of a negativity at about 100 ms that inverted in polarity at posterior sites and a widespread positivity at about 190 ms. These peaks were also quantified by averaging all data points within ±30 ms of the peak identified in the grand average. Similar to the word prime waveform, the picture waveform also consisted of a later negativity at about 400 ms and was quantified as the average of all data points between 300 and 500 ms.

The target epoch also began 100 ms prior to the onset of the stimulus and continued for another 1200 ms following it. The period prior to the onset of the target was not stable and differed between the two sleep conditions. Thus a 0–125 ms post-stimulus onset baseline correction was used. ERPs elicited by the target words in this short latency interval mainly reflect sensory processing and thus should not have been influenced by the extent of semantic association with the prime and only minimally by the amount of sleep. To assure that possible differences between conditions were not a result of baseline variability, the data were analysed relative the 0–125 ms a post-target baseline interval and again with the usual pre-stimulus baseline interval. Again, the single trial epochs were baseline corrected and any EEG activity exceeding ±100 μV on any channel were rejected from averaging. The P200 was quantified as the average of all data points between 170 and 230 ms. A large N400 was elicited by the unassociated targets. On the other hand, only a small amplitude N400 was elicited by the primed targets. Because a distinct N400 peak was not always apparent, the N400 was quantified as the average of all data points between 300 and 500 ms. A late positivity was also elicited after the N400. This late positivity was quantified as the average of all data points between 600 and 800 ms.

Electrode sites were grouped into regions of interest (ROIs), to include 12 electrodes over midline and lateral fronto-central areas (see Fig. 1), where the ERP components of interest are largest. These ROIs allowed for an analysis of an anterior-posterior and an inter-hemisphere factor. Specifically for the anterior-posterior electrode factor, four electrode sites in Column 1 (F3, C3, CP3, P3), Column 2 (Fz, Cz, CPz, Pz), and Column 3 (F4, C4, CP4, P4) were chosen for analysis. For the inter-hemisphere factor, three electrode sites in Row 1 (F3, Fz, F4), Row 2 (C3, Cz, C4), Row 3 (CP3, CPz, CP4) and Row 4 (P3, Pz, P4) were chosen for analysis. Separate ANOVAs were performed for the word and picture–word association tasks. Four-way ANOVAs with repeated measures on target association (strong/named, weak, unassociated), sleep (normal sleep, sleep deprivation), anterior-posterior (frontal, central, centro-parietal, parietal) and hemisphere (left, midline, right) site were run on each of the intervals for the prime and target data.

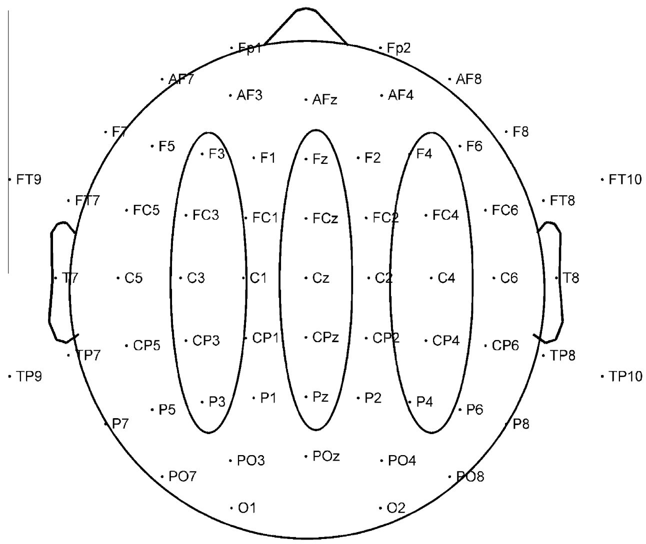

Fig. 1. Electrode montage and the circled regions of interest (ROIs) used for statistical analyses of the ERPs.

For all statistical analyses, a Geisser–Greenhouse correction procedure was used when appropriate (Geisser & Greenhouse, 1958).

3. Results

3.1. Stanford Sleepiness Scale

As expected, subjective ratings of sleepiness significantly increased following the sleep-deprived compared to the normal sleep condition. The mean subjective rating was 2.12 (SD = 0.82) following normal sleep and 6.18 (SD = 0.95) following sleep deprivation, $t(10) = 9.62$, $p < 0.01$.

3.2. Word association task

3.2.1. Behavioural data

The mean accuracy and RT data are presented in Table 1. As may be observed, accuracy was significantly affected by target type $F(2,18) = 6.27$, $p < .01$. Accuracy was higher following presentation of the strongly associated and lower following presentation of the weakly associated and unassociated targets. For all target types, accuracy did decrease slightly following sleep deprivation, but the difference compared to normal sleep was not significant, $F(1,9) = 1.02$, $p < .34$. The target type × sleep interaction was not significant, $F < 1$.

The RT data revealed similar effects. RT was faster for strongly associated than for weakly associated targets and slowest for unassociated targets, $F(2,18) = 52.11$, $p < .01$. RT was about 15 ms slower following sleep deprivation but the difference was not significant, $F < 1$. Similarly, the target type × sleep interaction was not significant, $F < 1$.

Table 1
Mean (SD in parentheses) accuracy and reaction time (in ms) during the word association task.

Prime-target association	Accuracy		Reaction time	
	NS[a]	TSD[b]	NS	TSD
Strong	0.91 (.09)	0.83 (.15)	613 (100)	631 (108)
Weak	0.75 (.12)	0.74 (.14)	666 (125)	678 (111)
Unassociated	0.82 (.14)	0.76 (.14)	739 (85)	762 (102)

[a] Normal sleep.
[b] Total sleep deprivation.

3.2.2. Physiological data

3.2.2.1. Target words. Fig. 2 illustrates the target ERPs following normal sleep and sleep deprivation. The target ERPs consisted of an initial positivity peaking at about 200 ms, followed by a large negativity at about 400 ms (N400). A later, long-lasting 600–800 ms positivity was also apparent. The mean amplitude of the P200, N400 and the late positivity at midline electrodes can be seen in Table 2.

3.2.2.1.1. P200. The positivity in the 170–230 ms interval was largest at frontal sites declining in amplitude at posterior sites. The amplitude of P200 did not significantly vary as a function of target type, $F < 1$. Sleep condition did not significantly affect P200, $F < 1$. The interaction between target type and sleep condition was also not significant, $F(2,18) = 1.50$, $p < .21$.

3.2.2.1.2. N400. The negativity in the 300–500 ms interval corresponding to N400 was largest at Cz and decreased in amplitude at anterior and posterior positions, $F(3,27) = 9.92$, $p < .01$. The differences between hemispheres was not significant, $F(2,18) = 2.42$, $p < .12$.

A main effect of target type was found, $F(2,18) = 36.01$, $p < .01$. N400 was largest following presentation of the unassociated targets and smallest following presentation of the strongly associated targets. Importantly, a main effect of sleep condition was also significant, $F(1,9) = 9.30$, $p < .01$. N400 was significantly larger following normal sleep than following sleep deprivation. The sleep condition × target type interaction was not significant, $F < 1$. Interactions involving sleep condition and electrode positions were not significant, $F < 1$.[1]

3.2.2.1.3. Late positivity. The positivity between 600 and 800 ms was largest at parietal regions and declined in amplitude at more anterior sites. It was significantly affected by target type, $F(2,18) = 6.59$, $p < .01$; it was smallest following presentation of the unassociated compared to either the weakly or strongly associated targets. Sleep condition did not affect the amplitude of this late positivity, $F < 1$ and the interaction between target type and sleep condition was also not significant, $F < 1$.

3.2.2.2. Prime words. A comparison of the processing of the initial prime words was also made. Fig. 3 illustrates the prime word ERPs following normal sleep and following sleep deprivation. The ERP waveforms in these conditions consisted of a central maximum positive deflection at about 200 ms that inverted in polarity at posterior sites. The amplitude of P200 was not affected by sleep condition, $F < 1$. The P200 was followed by a long-lasting anterior negativity from about 300 ms until the onset of the target. Sleep deprivation did affect this negativity; it was significantly attenuated following sleep deprivation, $F(1,9) = 4.85$, $p < .05$. As expected, the strength of the association of the subsequent target did not significantly affect the amplitude of either of the P200 or later negativity.

[1] It is possible that the inclusion of the multiple electrode data factor in the ANOVA might have smeared specific N400 effects. The ANOVAs were therefore rerun only on the Cz data, where N400 was largest. Again, the effect of target type was significant, $p < .01$. N400 was again significantly larger following normal sleep than sleep deprivation, $p < .01$. The interaction between sleep and target type remained non-significant. It is also possible that the use of the 0–125 ms post-stimulus baseline might have affected the results. The N400 data were therefore reanalyzed at Cz with a −100 to 0 ms pre-stimulus baseline. The effects of target type remained significant, $p < .01$. N400 was again significantly reduced following sleep deprivation, $p < .01$ and the sleep × target type interaction was again not significant.

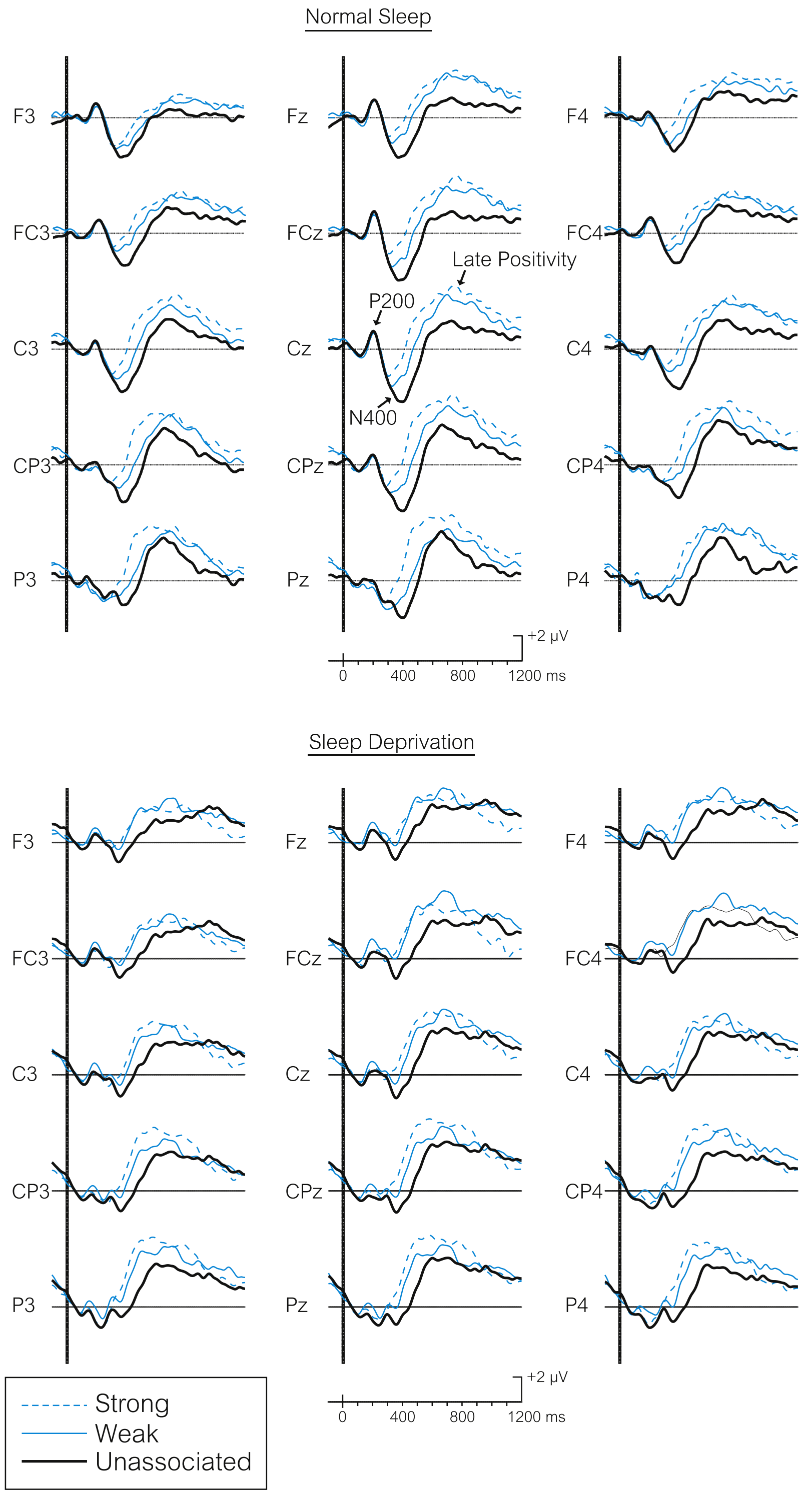

Fig. 2. Grand average (average of all subject's averages) ERPs to target words during the word association task. The targets were either strongly associated, weakly associated or unassociated with the previous prime word. In this and all other figures negativity at the scalp relative to the reference is indicated by a downward deflection. An early P200 was elicited by the target words. Its amplitude did not differ between normal sleep and sleep deprivation conditions. As expected, the amplitude of a later N400 was larger to unassociated and weakly associated targets, independent of the amount of sleep. Sleep deprivation did however result in a significant overall reduction in the amplitude of N400.

3.3. Picture association task

3.3.1. Behavioural data

The mean accuracy and RT data are presented in Table 3. Accuracy was higher following presentation of the targets that named the picture and lower for targets that were either weakly associated or unassociated with the picture, $F(1,10) = 9.09$, $p < .01$. The main effect of sleep condition was significant, $F(1,10) = 10.48$, $p < .01$, but there was also a target type × sleep condition interaction, $F(2,20) = 9.42$, $p < .01$. Simple main effects testing was used to

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Table 2
Mean (SD in parentheses) amplitudes (in µV) at midline electrodes following presentation of the target word during the word association task.

Prime-target association	Electrodes	Group	Time interval		
			170–230 ms	300–500 ms	600–800 ms
Strong	Fz	NS[a]	1.48 (2.51)	−0.14 (2.53)	4.34 (1.85)
		TSD[b]	1.63 (1.77)	1.81 (1.81)	4.24 (3.21)
	Cz	NS	1.39 (2.99)	−0.13 (3.68)	6.00 (1.94)
		TSD	0.75 (1.65)	2.09 (2.77)	6.00 (3.51)
	Pz	NS	−0.36 (2.17)	1.88 (3.84)	6.41 (2.51)
		TSD	−0.81 (1.78)	2.85 (3.41)	6.58 (2.93)
Weak	Fz	NS	1.44 (2.05)	−1.34 (2.58)	4.04 (3.38)
		TSD	2.22 (1.60)	0.75 (3.67)	4.40 (3.54)
	Cz	NS	1.30 (2.25)	−2.20 (3.40)	4.93 (3.85)
		TSD	1.30 (1.45)	0.43 (3.90)	5.70 (4.15)
	Pz	NS	−0.87 (1.46)	−1.27 (3.60)	4.79 (4.76)
		TSD	−0.06 (1.71)	1.33 (3.30)	5.57 (3.66)
Unassociated	Fz	NS	1.56 (2.44)	−3.26 (2.48)	1.67 (2.19)
		TSD	1.94 (3.24)	−0.58 (2.54)	3.28 (3.31)
	Cz	NS	1.52 (2.70)	−4.36 (2.67)	2.50 (3.17)
		TSD	0.89 (2.79)	−1.25 (2.56)	4.41 (3.41)
	Pz	NS	−0.16 (1.77)	−2.67 (2.32)	4.22 (3.79)
		TSD	−0.89 (2.62)	−0.84 (2.48)	4.85 (3.23)

[a] Normal sleep.
[b] Total sleep deprivation.

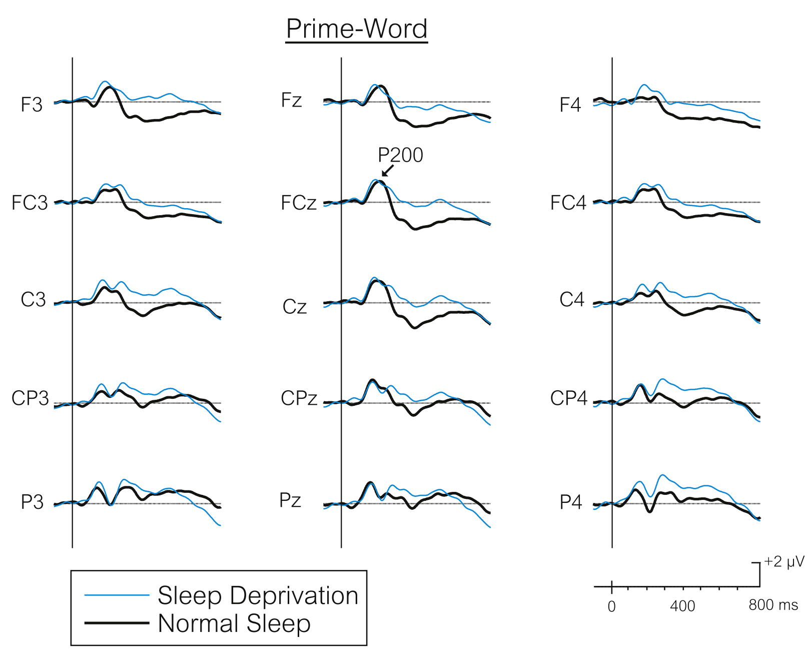

Fig. 3. Grand average ERPs to initial prime words during the word association task. The P200 elicited by the words was not affected by sleep. However, a long-lasting negativity beginning at 300 ms was much reduced following sleep deprivation compared to normal sleep.

Table 3
Mean (SD in parentheses) accuracy and reaction time (in ms) during the picture association task.

Prime-target association	Accuracy		Reaction time	
	NS[a]	TSD[b]	NS	TSD
Named	0.95 (.03)	0.92 (.08)	553 (67)	583 (84)
Weak	0.88 (.06)	0.77 (.02)	684 (96)	700 (84)
Unassociated	0.90 (.07)	0.85 (.09)	735 (95)	746 (62)

[a] Normal sleep.
[b] Total sleep deprivation.

determine the source of the interaction. Sleep deprivation resulted in a significant decline in accuracy of detection but only for weakly associated and unassociated targets. Sleep condition did not however significantly affect the accuracy of detection of targets that named the prime picture.

A significant effect of target type was also found for RT, $F(2,20) = 76.65$, $p < .01$. RT was fastest when the target word named the prime picture and slower for targets that were either weakly associated or unassociated with the prime picture. RT was about 15 ms faster overall following normal sleep compared to sleep deprivation, but the difference was not significant, $F(1,10) = 1.50$, $p < .25$. The target type × sleep condition interaction was also not significant, $F < 1$.

3.3.2. Physiological data

3.3.2.1. Target words. Fig. 4 illustrates the target ERPs following normal sleep and sleep deprivation. The morphology of the target word ERPs in the picture–word association task was similar to that

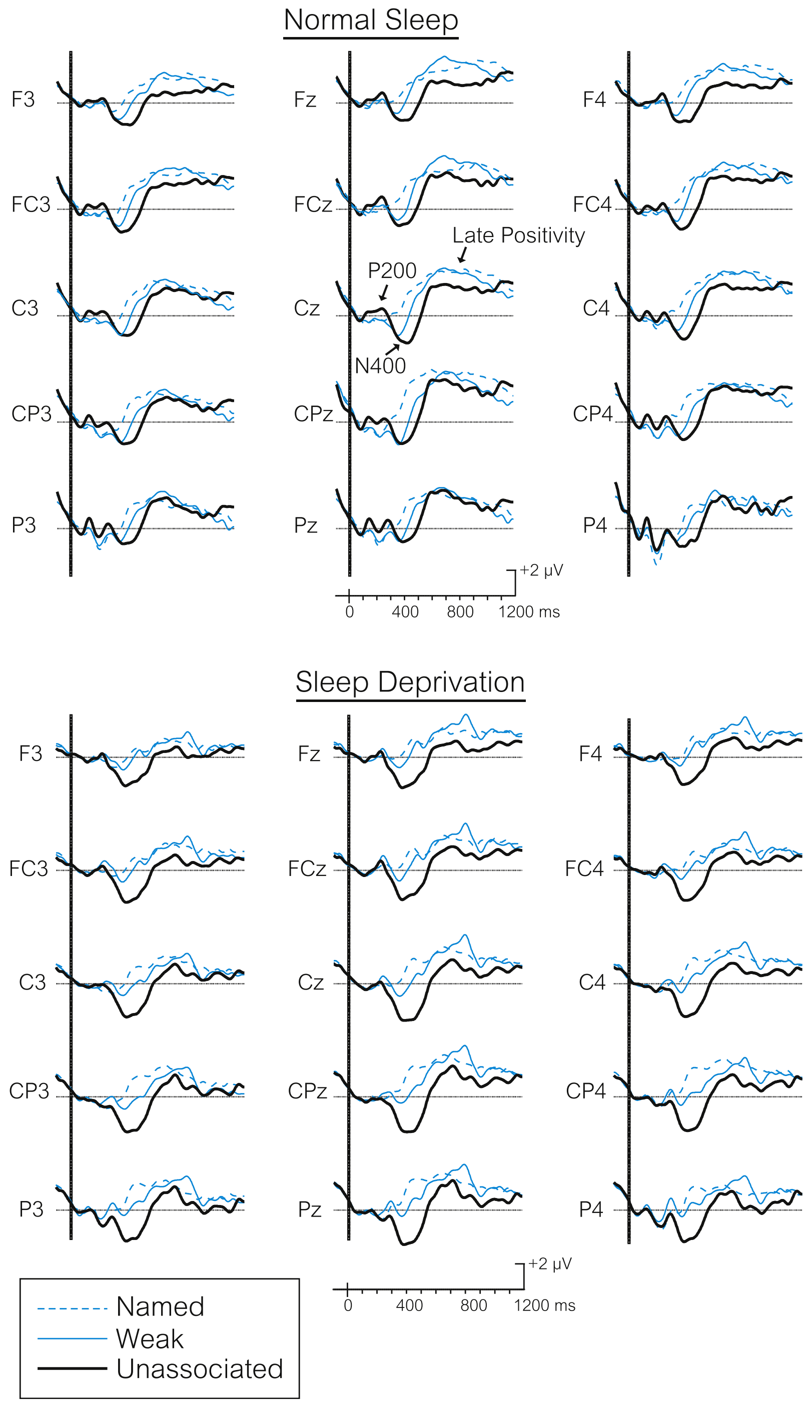

Fig. 4. Grand average ERPs to target words during the picture association task. In this paradigm, the targets either named the prime picture, were weakly associated or unassociated with the prime picture. Sleep condition did not affect the P200. Again, the amplitude of the N400 was affected by the extent of the association between the target and the prime in both the normal sleep and sleep deprivation conditions. The overall N400 was however not significantly reduced in amplitude in the sleep deprivation condition. This was unlike the case during the word association task.

observed for the target words in the word association task. It consisted of an initial positivity peaking at about 200 ms, followed by a large negativity at about 400 ms (N400). A later long-lasting 600–800 ms positivity was also apparent. The mean amplitude of these deflections can be seen in Table 4.

3.3.2.1.1. P200. The amplitude of P200 did not significantly vary as a function of target type, $F(2,20) = 1.71$, $p < .10$. Sleep condition did not significantly affect P200, $F < 1$ and the interaction between target type and sleep condition was also not significant, $F(2,20) = 1.43$, $p < .13$.

3.3.2.1.2. N400. As was the case with the N400 in the word association task, the N400 to the target word in the picture association task was largest at Cz and slightly decreased in amplitude at anterior and posterior positions. The differences between hemispheres was not significant, $F(2,20) = 1.78$, $p < .10$. A main effect of target type was found, $F(2,20) = 13.61$, $p < .01$. N400 was again largest following presentation of the unassociated targets and smallest for targets that named the prime picture. Contrary to findings in the word association task, the effect of sleep condition was not significant, $F < 1$. Thus, the amplitude of N400 did not significantly differ between the normal sleep and sleep deprivation conditions. The

Table 4
Mean (SDs in parentheses) amplitudes (in μV) at midline electrodes following presentation of the target word during the picture association task.

Prime-target association	Electrodes	Group	Time interval		
			170–230 ms	300–500 ms	600–800 ms
Named	Fz	NS[a]	0.03 (2.60)	1.70 (4.01)	4.34 (2.72)
		TSD[b]	0.16 (3.04)	1.07 (5.40)	3.18 (3.24)
	Cz	NS	−0.65 (3.43)	1.95 (5.53)	5.72 (2.88)
		TSD	−0.18 (3.39)	1.6 (6.59)	4.17 (4.00)
	Pz	NS	−1.83 (4.02)	2.34 (4.64)	4.38 (3.16)
		TSD	−0.80 (3.34)	2.36 (6.41)	4.12 (4.13)
Weak	Fz	NS	0.32 (2.78)	0.39 (3.91)	5.66 (4.88)
		TSD	0.22 (2.35)	0.03 (5.28)	3.90 (3.35)
	Cz	NS	−0.48 (3.78)	−0.69 (4.56)	5.94 (4.64)
		TSD	0.03 (3.01)	−0.33 (6.00)	4.58 (4.50)
	Pz	NS	−1.40 (4.88)	0.14 (4.62)	5.03 (4.43)
		TSD	−0.60 (3.58)	0.43 (5.47)	4.53 (4.82)
Unassociated	Fz	NS	0.80 (2.51)	−1.82 (3.06)	2.68 (3.14)
		TSD	0.87 (2.01)	−3.04 (4.26)	1.61 (3.67)
	Cz	NS	0.70 (3.24)	−2.74 (3.25)	3.93 (3.27)
		TSD	0.01 (2.71)	−3.9 (5.17)	2.28 (4.05)
	Pz	NS	−0.16 (3.85)	−0.98 (3.75)	4.63 (4.42)
		TSD	−0.72 (2.90)	−3.41 (4.75)	2.80 (3.60)

[a] Normal sleep.
[b] Total sleep deprivation.

sleep × target type interaction was again not significant $F(2,20) = 1.47$, $p < .26$. Finally, interactions involving sleep condition and electrode positions were not significant, $F < 1$ in both cases.[2]

3.3.2.1.3. Late positivity. The positivity between 600 and 800 ms was largest at parietal regions and declined in amplitude at more anterior sites. In contrast to the results from the word association task, it was not significantly affected by target type, $F < 1$. In addition, sleep condition did not affect the amplitude of this late positivity, $F(1,10) = 3.33$, $p < .09$, and the interaction between target type and sleep condition was also not significant, $F < 1$.

3.3.2.2. Prime pictures. Fig. 5 illustrates the ERPs after presentation of the picture following normal sleep and sleep deprivation. The initial largely exogenous, sensory processing of pictures was different compared to the processing of prime words. The picture waveform consisted of an anterior maximum negativity at about 100 ms that inverted in polarity at posterior sites and a widespread positivity at about 190 ms. A long duration negative-going DC shift beginning at about 50 ms and continuing until the onset of the target words was apparent in the sleep deprivation condition. This long-lasting negativity overlapped and summated with the other peak deflections. Thus, the initial 70–130 ms window was significantly more negative-going in the sleep deprivation condition, $F(1,10) = 4.62$, $p < .05$. The subsequent 160–320 ms and 300–500 ms intervals were also more negative-going in the sleep deprivation condition, but the differences compared to normal sleep failed to attain significance, $F(1,10) = 1.33$, and $F(1,10) = 2.08$, $p < .28$ and $<.18$, respectively. As expected, the strength of association of the subsequent target word had no significant effect on any of the prime picture ERPs, $F < 1$ in all cases.

[2] An ANOVA was also run only on the Cz data. Results were essentially identical to the multiple electrode findings. A main effect of target type was again observed, $p < .01$, with N400 being largest to the unassociated targets. N400 was again not significantly affected by sleep condition and the interaction between sleep and target type remained non-significant. Analysis at Cz with a −100 to 0 ms pre-stimulus baseline revealed similar results. The effects of target type remained significant, $p < .01$. Neither main nor interaction effects involving sleep condition were significant.

4. Discussion

Many studies have now indicated that sleep deprivation affects cognitive tasks that require effortful processing and the maintenance of sustained attention for successful completion (Killgore, 2010; Lim & Dinges, 2010; Ratcliff & Van Dongen, 2009). It has been suggested that subjects may be able to compensate for the effects of sleep deprivation by changing cognitive strategies, frequently by exerting additional compensatory effort. Functional imaging studies have provided support for the notion of flexibility of cognitive strategy and the fact that the brain does not react uniformly to cognitive demands following normal sleep and following sleep deprivation. Drummond et al. (2005) have proposed a cognitive demand-specific hypothesis to explain the maintenance of performance on many attention-demanding cognitive tasks. This hypothesis suggests that specific demands associated with a given cognitive task influence the cerebral response to that task following sleep deprivation. Compensation for the effects of sleep deprivation might involve the activation of spatially wider but similar areas of the brain that were activated by the task following normal sleep. It might however also involve the recruitment of additional resources from other brain regions not normally activated following normal sleep. Imaging studies have provided evidence for both types of activation (Chee et al., 2008; Drummond et al., 2005; Mander et al., 2008; Tomasi et al., 2009).

4.1. Word association task

The present study employed a semantic word priming task. This is a particularly interesting task for the study of the effects sleep deprivation because it can be carried out with different cognitive strategies, using either effortful processing requiring the maintenance of sustained attention or alternatively using automatic, effortless processing that is not dependent on the active maintenance of attention. The present study was optimised to permit the use of an expectancy-based, predictive strategy for task performance. The use of this strategy does however require vigilance and effortful processing in order to generate a list of possible target candidates based on the prime, and to keep them active in working memory prior to the onset of the target.

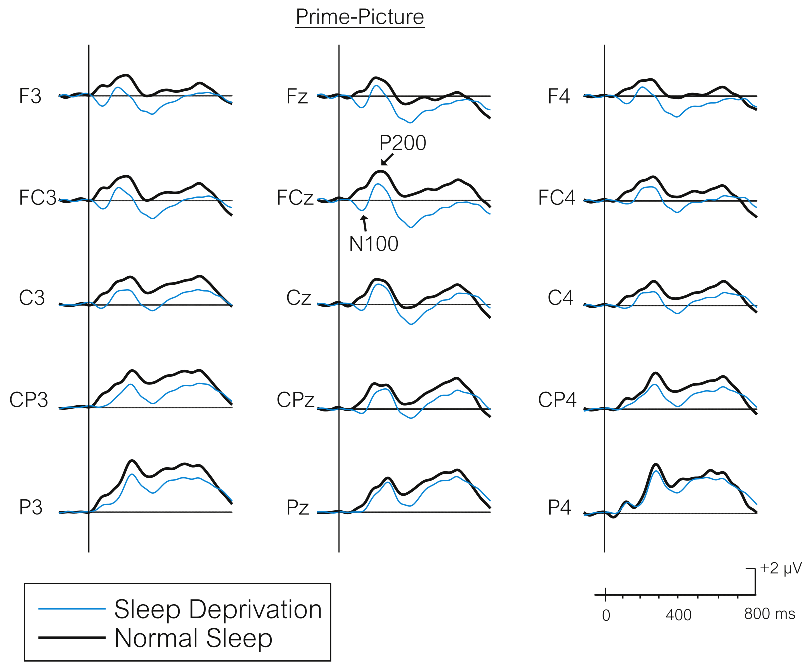

Fig. 5. Grand average ERPs to initial prime pictures during the picture association task. Following sleep deprivation, a long-lasting negative shift beginning at about 50 ms and lasting until the time of onset of the target was apparent. This negative shift overlapped and summated with the N100 and P200 deflections.

As expected, following normal sleep, a large priming advantage was observed – the strength of the semantic association between the prime and target words significantly affected both RT to and accuracy of detection of the target. Similarly, the amplitude of a central maximum N400 to the target word showed an inverse relationship with the strength of the semantic association, replicating the findings from previous studies (Holcomb, 1988; Kutas & Hillyard, 1980; Renoult, Brodeur, & Debruille, 2010). Sleep deprivation did result in an overall small, but non-significant deterioration in performance. Nevertheless, a strong priming advantage was still found. RT was still slower and the N400 larger to weakly associated and unassociated targets compared to strongly associated target following sleep deprivation.

How could performance using such an effortful and attention-demanding strategy not be affected by sleep deprivation? It is possible that subjects did exert the often-hypothesised additional compensatory effort to predict possible candidate target words that were associated to the prime and then to maintain these words in working memory. It is also possible however, that subjects switched cognitive strategies from one requiring considerable attention and effort when resources were available, to one that required less effort, relying instead on a more effortless, automatic activation of target candidates across a semantic network. Activation of this semantic network is less dependent on sustained attention or availability of cognitive resources.

The data appear to support the latter hypothesis: following sleep deprivation subjects might have relied on a more automatic mode of processing in order to make the semantic decision. Holcomb (1988) has observed that the amplitude of a target N400 is affected by the nature of task demands. He employed a semantic priming task in which the targets were either words or non-words. Some of the words were semantically associated with the word primes while others were not. When subjects were asked to make a lexical decision task (i.e., attention was directed away from the semantic association), N400 was still affected by the strength of the association between the prime and the target; it was larger when the target was semantically unassociated with the prime. Holcomb thus indicated that when subjects were engaged in an incidental lexical decision task, the semantic relationship between the prime and the target must have been processed automatically. In a different condition, subjects were asked if the target and prime were, in fact, semantically "related". If the N400 were solely dependent on automatic processing, then its amplitude would not have been affected by the directing of attention to the relationship between the target and prime. N400 did again vary indirectly as a function of the association between the prime and the target. Importantly, the N400 difference between the unrelated and related targets was significantly enhanced in the semantic compared to the lexical decision task. Thus, when the cognitive strategy involved an intentional but effortful search of the semantic network, N400 was larger compared to when it involved an incidental but effortless search. Importantly, a consistent N400 priming effect was maintained regardless of the strategy that was used. In the present study, a similar N400 pattern emerged: the overall amplitude of N400 was significantly reduced following sleep deprivation, although a priming effect was still maintained.

The use of different strategies involves a change of processing strategies *prior* to the onset of the target word. In keeping with the use of different strategies, ERPs following the onset of the prime word but prior to the target were different in the sleep deprivation and normal sleep conditions. A long-lasting negativity beginning at about 300 ms and continuing until the onset of the target word was significantly larger in the normal sleep condition. This might reflect the effortful prediction of candidate targets following the onset of the prime or alternately, the maintenance of these targets in working memory. The slow baseline negative shift might also be reflective of differences in a contingent negative variation (CNV)-like wave. The CNV is associated with the development of an expectancy wave following the onset of an initial, warning stimulus (S1) and a subsequent target (S2). The appearance of a CNV-like wave between the prime and the target in the normal sleep condition would be consistent with the expectancy/prediction strategy. It has long been known that the CNV is much attenuated following sleep deprivation (Naitoh, Johnson, & Lubin, 1971). In the sleep deprivation condition, the relative absence of an attention-demanding strategy that requires a prediction of and expectancy for the target following the onset of the prime word would also be consistent with a reduction in the amplitude of the CNV. The 2 s time constant might have attenuated some of the effects of the long duration slow wave. Nevertheless, because the time between the onset of the prime and the target was only 0.7 s, the effects of the time constant would have been minimal.

4.2. Picture association task

Although different cognitive strategies might have been employed for the word association task, this was probably not possible for the picture association task. The subject's task was to determine if a target word was semantically related to the previously presented picture. To do so required that the picture be initially named.

The seemingly fast and efficient naming of pictures obscures the complexity of the processes that are involved compared to the naming of words. A common model used to explain how pictures are named involves a dual-coding process including an initial non-verbal object representation-encoding (identification) of the complex features of a picture and the subsequent verbal picture naming (Francis, Corral, Jones, & Saenz, 2008; Johnson, Paivio, & Clark, 1996; Paivio, Clark, Digdon, & Bons, 1989). There is good evidence that the complex processes involved in picture naming require sustained attention. For example, Greenham, Stelmack, and Campbell (2000) presented subjects with a series of pictures on which words were superimposed. The words either named the picture or were semantically related or unrelated to it. When subjects were asked to name the pictures, it appeared that subjects also automatically named the words and made a semantic judgement about the nature of the picture–word relationship. N400 was larger to semantically unrelated words. In another condition, when subjects were asked to name the words, a priming effect was not found. N400 was not larger to unrelated pictures. Subjects could not concurrently automatically process the more complex but incidental pictures. The authors thus suggested that the initial processing of words occurs relatively automatically but the processing of pictures requires more effort and attention.

In the present study, the picture stimuli elicited a distinctive N100–P190 over anterior regions, inverting in amplitude over posterior regions. An additional overlapping and summating negative wave was apparent following sleep deprivation. This negative wave began about 50 ms after the onset of the prime picture and continued for another 300 ms. Many studies have now indicated that a similar negative shift occurs with an orientation of attention to visual stimuli (Hickey, McDonald, & Theeuwes, 2006; Hillyard, Di Russo, & Martinez, 2003; Nobre, Sebestyen, & Miniussi, 2000). The increase in amplitude of this long-lasting negativity following sleep deprivation would be consistent with the need for compensatory attention in order to encode and activate the name of the picture.

This initial difference in processing was unlike the case for the prime words, where differences occurred later and continued until the onset of the target. Because of the complexity involved in the generation of the name of a picture, it is unlikely that subjects would have sufficient time to also employ a predictive strategy to generate a list of candidate words associated with the picture even in the normal sleep condition. In the word–word association task, the overall N400 to the target stimuli was larger in the normal sleep than in the sleep deprivation condition. This is consistent with an effortful, expectancy/predictive strategy. On the other hand, in the picture–word association task, the overall N400 was not larger in the normal sleep than in the sleep deprivation condition. This lends further support to the notion that a predictive strategy was not used in this task.

The expected picture–word priming effect was again apparent for both performance and physiological measures following normal sleep. Thus, RT was longer, accuracy decreased and N400 was larger following target words that did not name the picture (i.e., words that were either weakly associated or unassociated with the prime picture). Sleep deprivation had a similar priming effect on both RT and N400. This was not the case for accuracy of performance. Sleep deprivation did not affect accuracy of detection for the target that named the picture. It did however affect accuracy of detection of the targets that did not name the picture, particularly for words that were weakly associated with the prime. This might be explained by the so-called dominant response hypothesis (Harrison & Horne, 2000). Performance on a task that requires the selection of a dominant, congruent response is not affected by sleep deprivation. The ability to select less dominant, but equally valid response alternatives is however affected (Gottselig et al., 2006; Heuer, Kohlisch, & Klein, 2005). In the present study, the dominant semantically associated target word would, of course, be one that named the picture. The non-dominant, but equally valid response would be a target word that was weakly associated with the picture, but did not name it.

The accuracy differences were not mirrored by the N400 results. The amplitude of N400 to the unassociated target was in fact larger in the sleep deprivation than in the normal sleep condition. The interaction between the sleep condition and the type of target was however not significant. This might be because of the amount of inter-subject variability in the amplitude of the N400 in this condition. The RT and N400 differences were quite consistent. The subtle differences between performance and N400 results have been observed elsewhere. The semantic processes that affect N400 may be not be completed in concomitance with behavioural performance (Kutas & Federmeier, 2011).

4.3. Conclusions

The cognitive processing involved in both the word and picture association tasks was affected by total sleep deprivation. In the case of the word association task, it would appear that under optimal levels of arousal, subjects might have relied on controlled, effortful processing to actively predict possible target word candidates following presentation of the initial prime word. The maintenance of such active processing probably cannot be sustained following total sleep deprivation. Our results suggest that subjects might thus have relied on a different strategy emphasising an automatic search of a semantic network in order to maintain performance. In the picture priming task, the use of an expectancy-based strategy is less effective. Moreover, the initial encoding and subsequent naming of pictures is more complex than for words. The naming of pictures probably requires more effort and attention than the naming of words. Our results suggest that following sleep deprivation, compensatory effort may still allow for the processing of the complex picture stimuli and thus the maintenance of the priming effect.

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References

Becker, C. A. (1980). Semantic context effects in visual word recognition: An analysis of semantic strategies. *Memory and Cognition, 8*(6), 493–512.

Bentin, S., McCarthy, G., & Wood, C. C. (1985). Event-related potentials, lexical decision and semantic priming. *Electroencephalography and Clinical Neurophysiology, 60*(4), 343–355.

Blackford, T., Holcomb, P. J., Grainger, J., & Kuperberg, G. R. (2012). A funny thing happened on the way to articulation: N400 attenuation despite behavioral interference in picture naming. *Cognition, 123*(1), 84–99.

Buysse, D. J., Reynolds, C. F., III, Monk, T. H., Berman, S. R., & Kupfer, D. J. (1989). The Pittsburgh Sleep Quality Index: A new instrument for psychiatric practice and research. *Psychiatry Research, 28*(2), 193–213.

Chee, M. W., Tan, J. C., Zheng, H., Parimal, S., Weissman, D. H., Zagorodnov, V., et al. (2008). Lapsing during sleep deprivation is associated with distributed changes in brain activation. *Journal of Neuroscience, 28*(21), 5519–5528.

Chwilla, D. J., & Kolk, H. H. (2005). Accessing world knowledge: Evidence from N400 and reaction time priming. *Brain Research, 25*(3), 589–606.

Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review, 82*(6), 407–428.

Corsi-Cabrera, M., Arce, C., Del Rio-Portilla, I. Y., Perez-Garci, E., & Guevara, M. A. (1999). Amplitude reduction in visual event-related potentials as a function of sleep deprivation. *Sleep, 22*(2), 181–189.

Deacon, D., Uhm, T. J., Ritter, W., Hewitt, S., & Dynowska, A. (1999). The lifetime of automatic semantic priming effects may exceed two seconds. *Brain Research, 7*(4), 465–472.

den Heyer, K., Briand, K., & Dannenbring, G. L. (1983). Strategic factors in a lexical-decision task: Evidence for automatic and attention-driven processes. *Memory and Cognition, 11*(4), 374–381.

Drummond, S. P., Bischoff-Grethe, A., Dinges, D. F., Ayalon, L., Mednick, S. C., & Meloy, M. J. (2005). The neural basis of the psychomotor vigilance task. *Sleep, 28*(9), 1059–1608.

Francis, W. S., Corral, N. I., Jones, M. L., & Saenz, S. P. (2008). Decomposition of repetition priming components in picture naming. *Journal of Experimental Psychology, 137*(3), 566–590.

Geisser, S., & Greenhouse, S. W. (1958). An extension of Box's result on the use of F distribution in multivariate analysis. *Annals of Mathematical Statistics, 29*(3), 885–891.

Gosselin, A., De Koninck, J., & Campbell, K. B. (2005). Total sleep deprivation and novelty processing: Implications for frontal lobe functioning. *Clinical Neurophysiology, 116*(1), 211–222.

Gottselig, J. M., Adam, M., Retey, J. V., Khatami, R., Achermann, P., & Landolt, H. P. (2006). Random number generation during sleep deprivation: Effects of caffeine on response maintenance and stereotypy. *Journal of Sleep Research, 15*(1), 31–40.

Greenham, S. L., Stelmack, R. M., & Campbell, K. B. (2000). Effects of attention and semantic relation on event-related potentials in a picture–word naming task. *Biological Psychology, 55*(2), 79–104.

Harrison, Y., & Horne, J. A. (2000). Sleep loss and temporal memory. *Quarterly Journal of Experimental Psychology, 53*(1), 271–279.

Heuer, H., Kohlisch, O., & Klein, W. (2005). The effects of total sleep deprivation on the generation of random sequences of key-presses, numbers and nouns. *Quartely Journal of Experimental Psychology, 58*(2), 275–307.

Hickey, C., McDonald, J. J., & Theeuwes, J. (2006). Electrophysiological evidence of the capture of visual attention. *Journal of Cognitive Neuroscience, 18*(4), 604–613.

Hillyard, S. A., Di Russo, F., & Martinez, A. (2003). The imaging of visual attention. In N. Kanwisher & J. Duncan (Eds.), *Attention and performance XX: Functional neuroimaging of visual cognition* (pp. 379–388). Oxford: Oxford University Press.

Hoedlmoser, K., Griessenberger, H., Fellinger, R., Freunberger, R., Klimesch, W., Gruber, W., et al. (2011). Event-related activity and phase locking during a psychomotor vigilance task over the course of sleep deprivation. *Journal of Sleep Research, 20*(3), 377–385.

Holcomb, P. J. (1988). Automatic and attentional processing: An event-related brain potential analysis of semantic priming. *Brain and Language, 35*(1), 66–85.

Hsieh, S., Tsai, C. Y., & Tsai, L. L. (2009). Error correction maintains post-error adjustments after one night of total sleep deprivation. *Journal of Sleep Research, 18*(2), 159–166.

Hurley, R. S., Paller, K. A., Wieneke, C. A., Weintraub, S., Thompson, C. K., Federmeier, K. D., et al. (2009). Electrophysiology of object naming in primary progressive aphasia. *Journal of Neuroscience, 29*(50), 15762–15769.

Huttenlocher, J., & Kubicek, L. E. (1983). The sources of relatedness effects on naming latency. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 9*(3), 486–496.

Johnson, C. J., Paivio, A., & Clark, J. M. (1996). Cognitive components of picture naming. *Psychology Bulletin, 120*(1), 113–139.

Keefe, D. E., & Neely, J. H. (1990). Semantic priming in the pronunciation task: The role of prospective prime-generated expectancies. *Memory and Cognition, 18*(3), 289–298.

Khateb, A., Pegna, A. J., Landis, T., Mouthon, M. S., & Annoni, J. M. (2010). On the origin of the N400 effects: An ERP waveform and source localization analysis in three matching tasks. *Brain Topography, 23*(3), 311–320.

Killgore, W. D. (2010). Effects of sleep deprivation on cognition. *Progress in Brain Research, 185*, 105–129.

Kiss, G. R., Armstrong, C., Milroy, R., & Piper, J. (1973). An associative thesaurus of English and its computer analysis. In A. J. Aitken, R. W. Bailey, & N. Hamilton-Smith (Eds.), *The computer and literary studies* (pp. 153–165). Edinburgh: University 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.

Kutas, M., & Hillyard, S. A. (1980). Reading senseless sentences: Brain potentials reflect semantic incongruity. *Science, 207*(4427), 203–205.

Lim, J., & Dinges, D. F. (2008). Sleep deprivation and vigilant attention. *Annals of the New York Academy of Sciences, 1129*, 305–322.

Lim, J., & Dinges, D. F. (2010). A meta-analysis of the impact of short-term sleep deprivation on cognitive variables. *Psychology Bulletin, 136*(3), 375–389.

Makeig, S., Bell, A. J., Jung, T. P., & Sejnowski, T. J. (1996). Independent component analysis of electroencephalographic data. In D. Touretzky, M. Mozer, & M. Hasselmo (Eds.), *Advances in neural information processing systems* (pp. 145–151). Cambridge: MIT Press.

Mander, B. A., Reid, K. J., Davuluri, V. K., Small, D. M., Parrish, T. B., Mesulam, M. M., et al. (2008). Sleep deprivation alters functioning within the neural network underlying the covert orienting of attention. *Brain Research, 1217*, 148–156.

Morris, A. M., So, Y., Lee, K. A., Lash, A. A., & Becker, C. E. (1992). The P300 event-related potential. The effects of sleep deprivation. *Journal of Occupational Medicine, 34*(12), 1143–1152.

Murphy, T. I., Richard, M., Masaki, H., & Segalowitz, S. J. (2006). The effect of sleepiness on performance monitoring: I know what I am doing, but do I care? *Journal of Sleep Research, 15*(1), 15–21.

Naitoh, P., Johnson, L. C., & Lubin, A. (1971). Modification of surface negative slow potential (CNV) in the human brain after total sleep loss. *Electroencephalography and Clinical Neurophysiology, 30*(1), 17–22.

Neely, J. H. (1976). Semantic priming and retrieval from lexical memory: Evidence for facilitatory and inhibitory processes. *Memory and Cognition, 4*(5), 648–654.

Neely, J. H. (1991). Basic processes in reading: Visual word recognition. In D. Besner & G. W. Humphreys (Eds.), *Semantic priming effects in visual word recognition: A selective review of current findings and theories* (pp. 264–336). Hillsdale, NJ: Lawrence Erlbaum Associates.

Nobre, A. C., Sebestyen, G. N., & Miniussi, C. (2000). The dynamics of shifting visuospatial attention revealed by event-related potentials. *Neuropsychologia, 38*(7), 964–974.

Paivio, A., Clark, J. M., Digdon, N., & Bons, T. (1989). Referential processing: Reciprocity and correlates of naming and imaging. *Memory and Cognition, 17*(2), 163–174.

Perrin, F., Pernier, J., Bertrand, O., & Echallier, J. F. (1989). Spherical splines for scalp potential and current density mapping. *Electroencephalography and Clinical Neurophysiology, 72*(2), 184–187.

Phillips, N. A., Segalowitz, N., O'Brien, I., & Yamasaki, N. (2004). Semantic priming in a first and second language: Evidence from reaction time variability and event-related brain potentials. *Journal of Neurolinguistics, 17*(2), 237–262.

Posner, M. I., & Snyder, C. R. R. (1975). Facilitation and inhibition in the processing of signals. In P. M. Rabbitt & S. Dornic (Eds.), *Attention and performance* (pp. 669–682). San Diego: Academic Press.

Ratcliff, R., & Van Dongen, H. P. (2009). Sleep deprivation affects multiple distinct cognitive processes. *Psychonomic Bulletin and Review, 16*(4), 742–751.

Renoult, L., Brodeur, M. B., & Debruille, J. B. (2010). Semantic processing of highly repeated concepts presented in single-word trials: Electrophysiological and behavioral correlates. *Biological Psychology, 84*(2), 206–220.

Scheffers, M. K., Humphrey, D. G., Stanny, R. R., Kramer, A. F., & Coles, M. G. (1999). Error-related processing during a period of extended wakefulness. *Psychophysiology, 36*(2), 149–157.

Smith, M. E., McEvoy, L. K., & Gevins, A. (2002). The impact of moderate sleep loss on neurophysiologic signals during working-memory task performance. *Sleep, 25*(7), 784–794.

Swann, C. E., Yelland, G. W., Redman, J. R., & Rajaratnam, S. M. (2006). Chronic partial sleep loss increases the facilitatory role of a masked prime in a word recognition task. *Journal of Sleep Research, 15*(1), 23–29.

Tomasi, D., Wang, R. L., Telang, F., Boronikolas, V., Jayne, M. C., Wang, G. J., et al. (2009). Impairment of attentional networks after 1 night of sleep deprivation. *Cerebral Cortex, 19*(1), 233–240.

Trujillo, L. T., Kornguth, S., & Schnyer, D. M. (2009). An ERP examination of the different effects of sleep deprivation on exogenously cued and endogenously cued attention. *Sleep, 32*(10), 1285–1297.