UNIVERSITAT ROVIRA I VIRGILI

REPRESENTATION AND PROCESSING OF AFFECTIVE WORDS: THE DISTINCTION BETWEEN EMOTION-LABEL AND EMOTION-LADEN WORDS

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FAIG CONSTAR que aquest treball, titulat "Representation and Processing of Affective Words: The Distinction Between Emotion-label and Emotion-laden Words", que presenta Ángel A. Betancourt Díaz per a l'obtenció del títol de Doctor, ha estat realitzat sota la meva direcció al Departament de Psicologia d'aquesta universitat.

HAGO CONSTAR que el presente trabajo, titulado "Representation and Processing of Affective Words: The Distinction Between Emotion-label and Emotion-laden Words", que presenta Ángel A. Betancourt Díaz para la obtención del título de Doctor, ha sido realizado bajo mi dirección en el Departamento de Psicología esta universidad.

I STATE that the present study, entitled "Representation and Processing of Affective Words: The Distinction Between Emotion-label and Emotion-laden Words", presented by Ángel A. Betancourt Díaz for the award of the degree of Doctor, has been carried out under my supervision at the Department of Psychology of this university.

Tarragona, February 2, 2024

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Dr. Pilar Ferré Romeu Dr. Marc Guasch Moix

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Abstract

This present thesis addresses the representation and the processing of affective words, focusing on the distinction between emotion-label words (e.g., fear) and emotion-laden words (e.g., death). The first aim of this thesis is to study the representation of affective words by examining how they are organized in the mental lexicon and identifying the features or characteristics that best describe them. The second aim is to investigate the processing of affective words, by examining whether emotional valence behaves as a feature of semantic richness, and whether the pattern of results is the same for emotion-label and emotion-laden words. To address these goals, we conducted three studies. In the first study, we analyzed the associative structure of emotion-label, emotion-laden and neutral words through a word association task. In the second study, we developed a semantic space to define the organization of emotion-label, emotion laden and neutral words, and examined which are the characteristics that best predicts the word category. Finally, in the third study, emotion-label, emotion-laden and neutral words were tested in a lexical decision task to examine whether valence behaves as a feature of semantic richness and whether valence effects differ between emotion-label words and emotion-laden words. The general conclusion of the thesis is that valence is the central dimension of the affective content of words, although it cannot distinguish between the two types of affective words (emotion-label words and emotion-laden words), whereas multi-componential theories can do so.

PART I

INTRODUCTION

CHAPTER I: Theoretical Background

1.1 Opening

The human language and emotion systems are key to everyday communication. The emotions we experience can affect our language production and comprehension. Our internal affective states can also be expressed lexically. Therefore, within a language, we have words that allow us to communicate many things, including emotions. Words that communicate emotions are often referred to as affective words. There is a relevant distinction between two types of affective words: emotion-label words (or simply emotion words) and emotion-laden words. The emotion-label words (EM words henceforth) directly refer to a specific emotion, that is they denote an emotion (e.g., "sadness," "happiness"), while emotion-laden words (EL words henceforth) do not explicitly refer to an emotion but can elicit it (e.g., "death," "birthday"; Pavlenko, 2008). Studying how we represent, and process affectively loaded words can help us to understand the complex relationship between language, cognition, and emotion. Several research lines can be explored to gain insights into this relationship.

First, we can study how affective words are organized in our mental lexicon and how different affective variables influence the way they are organized. Word association studies are a useful tool for assessing the structure of semantic memory and the organization of words in the lexicon (De Deyne et al. 2013; Steyvers et al. 2005; Vivas et al. 2019). In addition, emotion research has devoted much effort to investigating the dimensionality of the emotion domain and how different emotion concepts are represented within this dimensional space (Fontaine et al. 2007; Troche et al. 2017). Another important area of study focuses on how affective words are processed and whether they differ from words that are not affectively loaded (El-Dakhs et al. 2019; Wang et al. 2019; Wu et al. 2019). Finally, there are several models of emotion that try to explain the complex relationship between language and emotion. One of the most widely accepted models suggests that emotions can be characterized along several dimensions, with valence, and arousal as the most relevant (Russell, 1980). Other theories suggest that the experience of emotion is a complex evaluative process that involves multiple components (Scherer et al. 2001a).

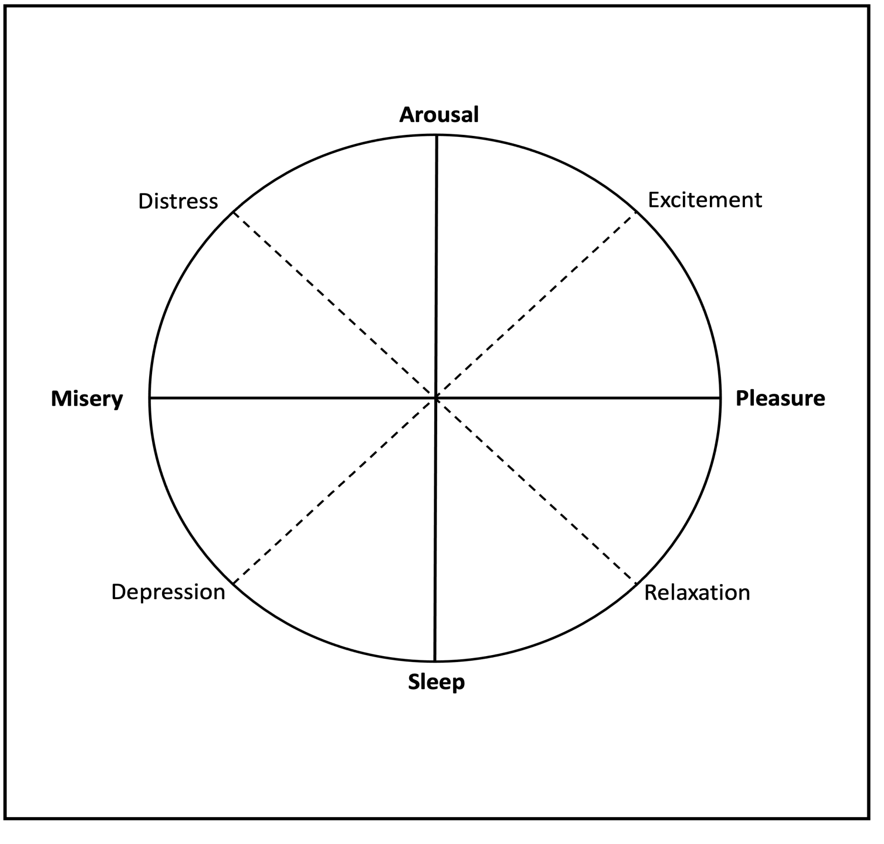
The introduction of the thesis has two main parts. In the first part, two of the most influential theories of emotions are introduced: the two-dimensional theory (Russell, 1980) and the Component Process Model (Scherer et al. 2001a), which are the framework of this study. In the second part, the most important research in affective word processing is reviewed, with a focus on the distinction between emotion-label words and emotion-laden words.

1.2 Dimensional Accounts of Emotions

One of the initial developments of the dimensional models of emotion can be attributed to Wundt (1896). He suggested that the affective meaning of words can be organized along three primary axes: pleasantness-unpleasantness, arousing-subduing, and strain-relaxation. This proposal inspired similar models. Various dimensional models were developed with some differences in how these dimensions are related to each other (Larsen & Diener, 1992; Russell, 1980; Watson & Tellegen, 1985). Russell's (1980) Circumplex Model of Affect emerged as one of the most accepted frameworks for the assessment of the subjective experience of emotions. This model uses a circle intersected by two axes (see Figure 1) to describe the affective structure of the emotional experience (Russell, 1980, 2003; Russell & Barrett, 1999). The cognitive structure of affect was summarized by Russell (1980), in terms of eight variables that fall in a two-dimensional circle. The horizontal dimension represents what was later called valence, which goes from misery (later called unpleasantness) to pleasure (later named pleasantness). The vertical dimension represents the arousal dimension, which goes from arousal (later known as high arousing) to sleep (later known as low arousing). The other four variables, while not establishing separate dimensions, help to define the quadrants of the space. Each of the remaining four variables marks the precise intersection between two dimensions. For example, “relaxation” is situated exactly between sleep (low arousing) and pleasure (pleasantness).

Therefore, within the circumplex structure we can represent the affective properties of different types of stimuli, including affective words and facial expressions, among others. In this sense, with the circumplex representation, the similarities and differences between various stimuli are evidenced by their proximity around the perimeter of the circle. For example, closely positioned items are more similar to each other, while those separated by 180 degrees stand as complete opposites. Under this view every individual stands at some point of the circumplex when confronted with affective situations (i.e., responding to internal and external events; Russell, 2003).

Figure 1. Circumplex Model of Affect



NOTE: Adapted from Russell, 1980.

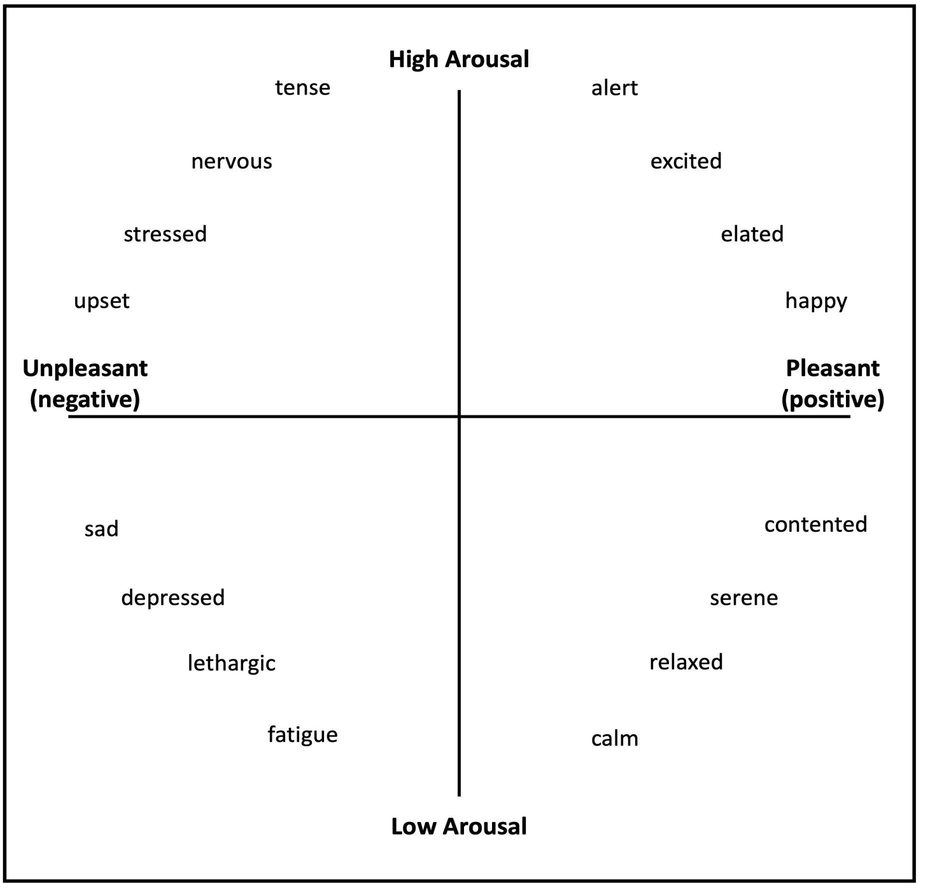
According to the Circumplex Model of Affect, the complexity of the structure of emotion is reduced to a small number of underlying dimensions, commonly referred to as *core affect*. This concept differs from the generic use of "affect" that broadly refers to any emotional state (Barrett, 2006). The term "core" implies that this form of affective response represents the "core" or more basic and rawer affective (emotional) experience. Therefore, core affect represents a fundamental type of emotional understanding that is intrinsic to each individual (Barrett, 2006; Barret & Russell, 1999). It is defined as a neurophysiological state that is always available to consciousness. In essence, core affect serves as a measure of our current affective state, providing a common metric that facilitates the comparison of a range of psychological and behavioral processes, from reflexes to complex decision making (Russell, 2003; Russell & Barrett, 1999).

Based on the notion of core affect, affective experience unfolds as a dynamic interplay between our internal states and external stimuli. Core affect acts as a barometer of the individual's relationship with the environment and with his/her internal feelings (Barrett, 2006). For example, when we encounter a stimulus (person, event, object, word, etc.), our core affect is immediately engaged and sets the emotional tone for our perceptual experience. During this interaction, the *affective quality* (the intrinsic emotional character) of the stimulus can modify our core affect even before we are fully conscious of the stimulus itself. Therefore, when a person confronts an event, core affect begins to change immediately, even before the event is consciously registered. In essence, the affective quality of the stimulus acts as a precursor to the core affect that we subsequently assign to the stimulus (the core affect assigned to a stimulus is known as *attributed affect*), which in turn contributes to the unfolding of an *emotional episode*. An emotional episode is an event that counts as an instance of emotion and consists of various components that include not only core affect, but also physiological, behavioral, and conscious experiences. Thus, core affect is not static, and it is shaped by perceptual, cognitive, and evaluative processes that form our affective experience. Consequently, core affect is not seen as a simple measure of our moment-to-moment emotional state, but as a central component of an emotional episode, that is both influenced by immediate sensory experience, and influences the more complex processes of the emotional experience construction (Russell, 2003).

From this perspective, core affect is available to consciousness through the integration of two bipolar dimensions: *valence* and *arousal*. Valence corresponds to the degree to which a state is pleasant/positive (e.g., happy; content) or unpleasant/negative (e.g., sad; angry), while arousal refers to the degree to which a state is experienced as activating (e.g., excited; agitated) or calming (e.g., calm; relaxed). Valence is often used to describe the positive or negative character of an emotion (Charland, 2005; Colombetti, 2005). Specifically, valence is related to the hedonic tone (the degree of pleasantness, neutrality, or unpleasantness) of the subjective experience of emotions, ranging from highly negative/unpleasant emotions, such as fear or disgust, to extremely positive/pleasant emotions, such as enthusiasm or joy (Colombetti, 2005; Russell, 2003). Thus, valence describes an attribute of the subjective experience of emotions, that can be summarized as how well one is doing (Russell & Barrett, 1999). On the other hand, arousal refers to the level of bodily (psychological and physiological) activation or intensity associated with an emotional state (Lang & Davis, 2006). In this context, arousal is defined as a characteristic of the intensity of an internally experienced emotion (Russell, 2003). In addition, both valence and arousal have their underlying physiological correlates. In this context, valence can be seen as intrinsic attractiveness (positive valence) or averseness (negative valence) of an object, event, or situation and it is supported by complex physiological and neurophysiological systems that differentially engage specific brain networks for processing positive (e.g., midbrain and ventral striatum) and negative (e.g., dorsolateral prefrontal cortex, anterior midcingulate cortex) emotional stimuli. Similarly, arousal is also regulated by a complex network of brain structures and systems (e.g., amygdala, hippocampus). These are key areas for the experience of pleasure and reward and amplify our ability to respond to emotionally relevant stimuli (Ascheid et al. 2019; Colibazzi et al. 2010; Costanzi et al. 2019; Haj-Ali et al. 2020; Moseley et al. 2012; Styliadis et al. 2018).

In general all affective states can be plotted along valence and arousal (see Figure 2; Barrett, 2006; Barrett & Russell, 1999). The two-dimensional structure of emotion argues that the states we call happy, sad, angry, or calm can be reduced to the psychological and physiological dimensions of pleasure (valence) and activation (arousal). Therefore, for Russell & Barrett (1999) these two dimensions are the only necessary variables to describe any emotional state, suggesting that any emotion is an instance situated within the core affect and, similarly valenced/arousing emotions are not distinct in nature. Hence, "fear" might be the label for negative valence in situations involving risk, while "anxiety" could be the label used for a similar negative valence experienced in scenarios of uncertainty. The latter means that what differentiates those two emotions is the situation in which they appear, partly arising from cultural knowledge about emotions. Consequently, emotions are not discrete categories but continuous experiences that vary in valence and arousal.

Figure 2. The two-dimensional structure of affect.



NOTE: The two-dimensional structure shown in Figure 2 is an idealization of the circumplex, showing a few basic affective states that define its perimeter. Within the perimeter we can also plot more affective states such as fear, joy, guilt, or disgust (adapted from Barrett & Russell, 1998).

How do the core affect dimensions of emotion, valence and arousal, relate to each other? The relationship between valence and arousal within a two-dimensional framework is typically expressed as a U-shaped curve (Bradley & Lang, 1999; Ferré et al. 2012; Guasch et al. 2016). A U-shaped relationship indicates that arousal levels tend to increase together with the intensity of the emotional content. For instance, experiencing emotions that are highly negative and positive, typically corresponds with high levels of arousal. Consider, for example, the core affective states of upset (negative and high arousal) and happy (positive and high arousal). Moreover, neutral stimuli are often associated with low levels of arousal (e.g., bench or notebook). Thus, the presence of a positive or negative stimulus (like a word) is generally associated with an increase in various excitatory processes, both behavioral and physiological, leading to an increased sense of activation and alertness. Focusing on words, the U-shaped relationship between valence and arousal is stronger for negative words, which tend to show high levels of arousal as they become more negative, whereas positive words show more variability, with some very positive words not eliciting high levels of arousal (Guasch et al. 2016). Furthermore, some researchers disagree with the U-shaped relationship, arguing that the association between valence and arousal is highly variable (Yik et al. 2023).

Most of the research framed on the two-dimensional model of the structure of emotions has assessed the emotional response produced by emotional stimuli, like facial expressions, pictures, and words. These studies have consistently shown that affective experience is best represented by two variables: valence and arousal. For example, in the seminal study of Bradley and Lang (1999), the role of three primary emotional dimensions in the definition of the affective space of words was examined: pleasure, arousal, and dominance. The authors reported that valence and arousal accounted for most of the variance in emotional word ratings. These results are also consistent with those of Osgood et al. (1957) who found that valence and arousal were the most important factors for semantic differentiation.

Inspired by the work of Bradley and Lang (1999), a series of normative studies across languages have relied on valence and arousal to describe the affective content of words (e.g., Ćoso et al. 2019; Guasch et al. 2016; Monnier et al. 2014; Montefinese et al. 2014; Soares et al. 2012; Stadthagen-Gonzalez et al. 2017; Warriner et al. 2013; Yao et al. 2017). In these studies, valence and arousal values of words are often obtained using self-report measures. These measures are essential for assessing the subjective affective interpretation of a word. Self-report measures of the subjective valence and arousal of words have been shown to be reliable across contexts and stimuli (Barrett, 2004). Therefore, these measures provide researchers with valuable data that can give insights into the affective experience of the individuals. This approach allows researchers to convert the subjective experiences of valence and arousal into numbers that can be analyzed to better understand how people process and represent words in their minds. Many researchers assess valence and arousal using a 9-point rating scale (Guasch et al. 2016; Hinojosa et al. 2016; Redondo et al. 2005; Redondo et al. 2007; Stadthagen-Gonzalez et al. 2017). In the case of valence, 1 indicates that the word is very negative/unpleasant and 9 indicates that the word is very positive/pleasant, while in the case of arousal, 1 indicates that the word is very calming and 9 indicates that the word is very exciting. Others evaluate valence using a -3 to +3 scale (with -3 and +3 defining the ends of a bipolar scale; positive to negative), and arousal using a 1-5 scale (ranging from calms to excited; Schmidtke et al. 2014). This is a structured and quantifiable approach to understand the affective connotations associated with different words as subjectively perceived by participants. Based on this two-dimensional perspective, most psycholinguistic research has focused on understanding the role of affective properties (valence and arousal) in word processing (Hinojosa et al. 2020a; Wu & Zhang, 2020).

Research about affective word processing has been the majority in the field. In contrast, the role of valence and arousal in the organization of affective words in the lexicon has hardly been studied. There are only two word association studies that have examined this issue. In the word association task, researchers ask participants to quickly respond to a cue word (i.e., “aggressive”) with the first word (associated word, i.e., “bad”) that comes to their mind (Coronges et al. 2007; Vivas et al. 2019). Using this method, Van Rensbergen et al. (2015) examined the extent to which the cue words and their associates share similar characteristics. They found that the valence and arousal of the cue words were important predictors of the valence and arousal of the associated words. In a similar study, Buades-Sitjar et al. (2021) found that the affective properties of the cue words (i.e., valence and arousal) strongly predicts the value of those same properties in the associated words. These studies evidence the relevance of affective variables in the organization of the associative structure of words in the lexicon. However, there are only two studies, and they have not distinguished between EM and EL words.

Two-dimensional models provide a valuable framework for understanding the structure of emotions. They can help to characterize both EM and EL words. For instance, the EM word *miedo* (fear) and the EL word *cadáver* (corpse), are both characterized by a negative valence and high levels of arousal. On the other hand, the EM word *pasión* (passion) and the EL word *premio* (award) are examples of positive valenced words with high arousal levels. However, since both, EM and EL words, can be equally characterized in terms of valence and arousal, two-dimensional models are not capable of differentiating between these two types of affective words. Importantly, previous studies have reported processing differences between EM and EL words (Kazanas & Altarriba, 2015; Knickerbocker & Altarriba, 2013; Pavlenko, 2008). However, these differences cannot be attributed to valence and arousal. Therefore, in order to correctly differentiate EM and EL words in terms of their affective content we need to consider other affective variables. To address this limitation, we focus on affective variables derived from a multi-componential conception of emotions (Arnold, 1960; Lazarus, 1966; Scherer, 2001a, b), which provides a more granular and detailed account of the emotional experience.

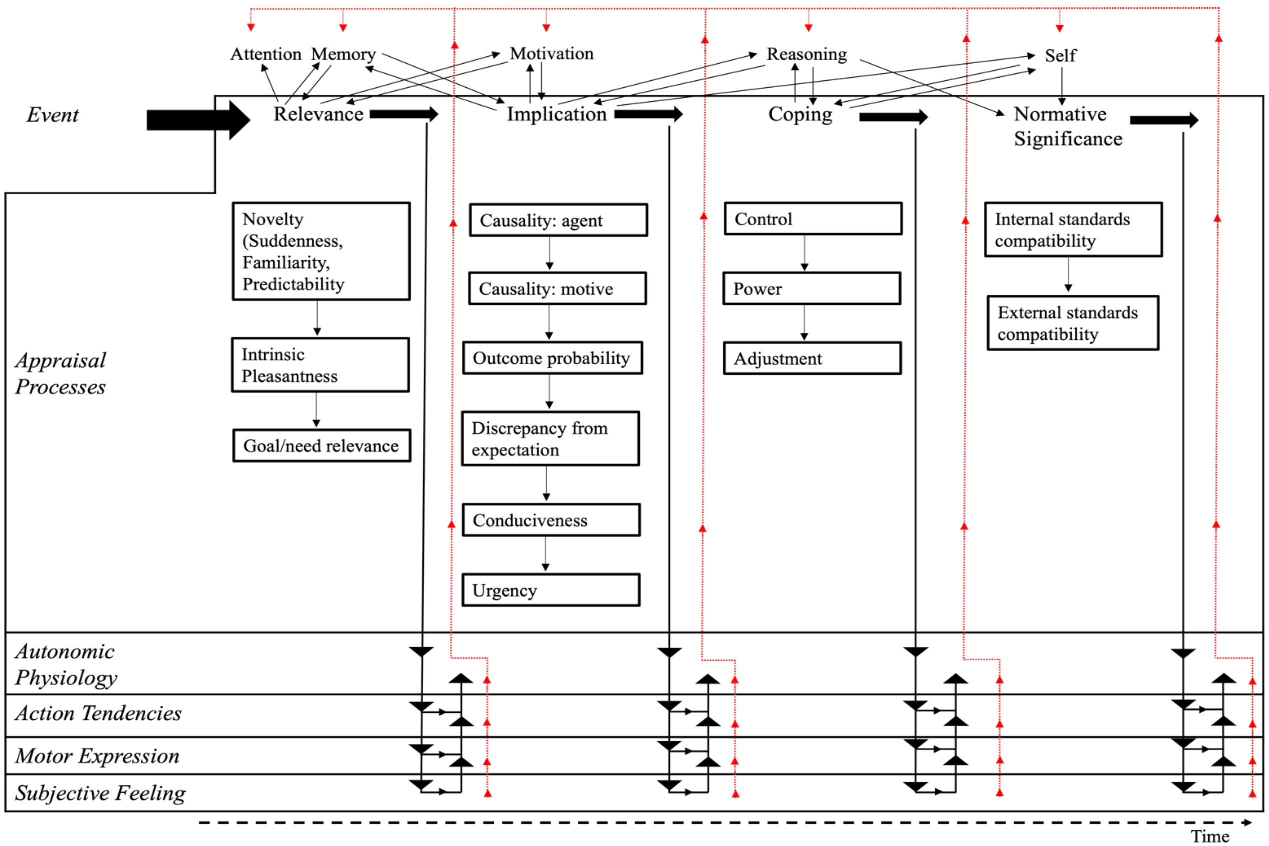
1.3 Component Process Model of Emotions

A set of influential theories of emotion are Appraisal Theories. Their basic premise is that emotions are defined as a process that involves evaluations and subjective interpretations of events (Arnold, 1960; Lazarus, 1966). Therefore, these theories generally assume that appraisal (or the evaluation of an event) is a central component of the emotion process. Inspired by Arnold, (1960) and Lazarus (1966), different authors followed this approach. Scherer (1982) defined emotions as a process that involves changes in multiple subsystems. This proposal assumes that the different components involved in the emotion process are not independent. Instead, they are jointly driven by a set of common factors that interact and influence each other, demonstrating a dynamic and recursive emotional response triggered by events that are highly relevant to the need, goals, and relevance of an individual.

According to Scherer and co-workers , emotions are a combination of multiple components that interact with different response mechanisms; this proposal is called the Component Process Model (CPM) (Scherer, 2009; Scherer et al. 2001a,b; Scherer, 1982), and it is based on evolutionary theory. The model proposes that emotions are comprised of five interrelated components: cognitive appraisal, physiological activation, motor expression, action tendencies, and subjective feeling (Scherer, 1984a, b). These five components are recursively interrelated and engaged in a constant evaluative process. The output of this process is the response to the evaluation process of an external or internal stimulus, culminating in an emotion episode (see Figure 3; Sander et al. 2018; Scherer, 2009; Scherer et al. 2001a). As shown in Figure 3, the CPM suggests that the emotion eliciting event and its outcomes are evaluated with a set of components on multiple levels of processing.

Therefore, the different components play a central role in the emotion eliciting process. The appraisal component is the major determinant of the emotion elicitation. It is an ongoing process that involves a consistent evaluation and re-evaluation of the environment. The CPM proposes a set of four criteria within the appraisal component, called stimulus evaluation checks (SECs), which are the basic building blocks that an organism needs to reach the significance of a stimulus. The type and the intensity of the elicited emotion depends on the results of the SECs. They relate to important classes of information about an object/event that an organism needs in order to prepare an appropriate response (Sander et al. 2005; Scherer, 2009; Scherer et al. 2001a).

Figure 3. Comprehensive illustration of the component process model (CPM).



NOTE. Adapted from Scherer (2009).

The *relevance* check includes the evaluations that occur earliest in the emotion experience and thus tend to be universal. It contains three levels where the organism considers how relevant the event is and whether it directly affects it or its social reference group. It considers the novelty of the stimuli, how pleasant or unpleasant (or how positive or negative) it is and whether it is related to its goals or needs.

The second check is the *implication* check. It is initiated after the relevance check. The information considered here is related to the implications and consequences of the emotion-evoking event and how it affects the individual's well-being and immediate or long-term goal. The implication check includes a set of 6 appraisal levels: 1) causality: agent, where the organism attempts to identify whether the causes of the event are external, 2) causality: motive, where the organism attempts to identify whether the causes of the event are internal, 3) outcome probability, in here the organism evaluates the likelihood or certainty of distinct outcomes to an event, 4) discrepancy form expectation, it refers to the congruence or discrepancy between the event and the individual's expectation at that moment, 5) conduciveness, the organism needs to check the conduciveness to assess whether the outcome of the eliciting event facilitates or prevents our goals and needs, and 6) urgency, which refers to an adaptive response to an event (Sander et al. 2005; Scherer, 2009; Scherer et al. 2001a).

The third appraisal process is the *coping* check. This is where the organism asks how well it is coping or adapting to the consequences of the implication check. Ultimately, this leads to identifying the most effective coping strategy for a situation. Coping check has three levels: 1) control, 2) power, and 3) adjustment. The control level centers on assessing whether the event or its outcome can be influenced by us or some external agent. Power, the second level within the coping check, refers to the power of the organism to take control or get others to help. After the power level, the organism evaluates the adjustment level, which represents the final stage of the coping check. After using all available methods of intervention, the organism can either adapt to, adjust, or cope with the consequences of an event (Sander et al. 2005; Scherer, 2009; Scherer et al. 2001a).

The final appraisal check is referred to as *normative significance*. In here, individuals evaluate how the eliciting event and their behavioral responses align with their values, ethics, cultural expectations, among others. The final appraisal (normative significance) takes place at two levels: 1) internal standards compatibility, and 2) external standards compatibility. On the internal standards compatibility level, the organism evaluates how an action meets internal standards such as the ideal self-image or moral beliefs. The second and final level of the normative significance check is external standards compatibility. Here, the organism evaluates the event and its own behavior in relation to the standards or demands from external environment including social groups, privileges, desired outcomes, and acceptable behaviors (Sander et al. 2005; Scherer, 2009; Scherer et al. 2001a).

The architecture of the model assumes a bidirectional influence between appraisal and various cognitive functions and motivational mechanisms, including attention, memory, motivation, reasoning, and self-concept (Scherer, 2009). These mechanisms provide prior information and evaluation criteria that are essential to the appraisal process. Therefore, a number of cognitive and motivational factors influence the appraisal process, affecting various mechanisms. The result of the appraisal process drives a response pattern into other components. This process initiates an ongoing recursive process that generates outputs aimed at providing adaptive responses that align with the results of the current appraisal (see Figure 3). In this sense, the appraisal component plays a crucial role in initiating and shaping the emotion experience, but it is also influenced by the feedback from the other components (Grandjean et al. 2008; Sander et al. 2018; Scherer et al. 2001a). Hence, physiological changes, action tendencies, motor expressions, and subjective feelings all provide information that can feed back into the appraisal process.

The autonomic physiology (physiological activation) component is in charge of bodily changes. It is related to involuntary responses to emotions such as changes in heart rate, breathing, blood pressure, and muscle tension. The physiological changes prepare the body for action and reflect the intensity of the emotional experience. On the other hand, the action tendency component refers to internal motivations that drive us to act in certain ways during emotional experiences. It involves readiness to act in response to an emotion. These tendencies can be to approach, avoid, or engage in some behavior that aids the individual to achieve a specific goal. The fourth component is motor expression. This component is related to external manifestations of emotion, such as facial expressions, vocal tones, body movements, body language, gestures, and posture. It can include reflex-like responses, overlearned motor patterns, and voluntary, goal-oriented expressions (Sander et al. 2005, 2018; Scherer et al. 2001a; Scherer et al. 2019). Finally, the fifth component is called subjective feeling. It plays a crucial role in the emotion process because it has integrative and regulatory functions over the previous components. The subjective experience of feeling synthesizes the outputs of the preceding components (appraisal processes, autonomic physiology, action tendencies, and motor expression) into a unified representation. This integrated central representation eventually becomes conscious and constitutes the subjective experience of feeling (Scherer, 2004). In general, the CPM highlights the dynamic interplay between these components (appraisal processes, autonomic physiology, action tendencies, motor expression, and subjective feeling), conceiving emotions as a complex and multi-componential process.

In comparison to the dimensional approach, the CPM model has scarcely been used to characterize affective words. The few studies that have used this approach have focused on EM words. These studies have challenged the reduction of emotions to two dimensions (Fontaine et al. 2007; Gillioz et al. 2016; Scherer, 2005). For example, Fontaine et al. (2007) found that a four-dimensional structure (evaluation-pleasantness, potency-control, activation-arousal, and unpredictability) is needed for an accurate representation of the semantic space of emotion words. Similarly, in a recent study, Ferré et al. (2023) evaluated the importance of the CPM components (appraisal, physiological response, action tendencies, motor expression, and feeling) in characterizing EM words. The authors found that feeling and interoception (physiological activation) were the most relevant predictors of emotion prototypicality (i.e., the extent to which a word is a good exemplar of the category "emotion"), suggesting that these two variables are critical in the characterization of words denoting emotions. However, these studies have focused on EM words and have not considered EL words. In this sense, the CPM components could help us to better characterize emotion-laden words and to differentiate between both types of affective words, considering that they cannot be distinguished in terms of valence and arousal.

Overall, the characteristics of affective words have been traditionally described in terms of valence and arousal, but these variables cannot distinguish EM and EL words. Variables derived from CPM models might be useful in this sense. However, research in this field is very limited. The processing of affective words has been much more investigated. In the next chapter, we review the influence of different affective variables in word processing and the similarities and differences between EM and EL words.

CHAPTER II: Studies on affective word processing

2.1 Valence and Arousal

Numerous behavioral studies have examined the effects of emotional valence and arousal on word processing, with mixed findings. One of the most widely used tasks to study these effects is the lexical decision task (LDT). The LDT is a common task in psycholinguistics, used to assess word recognition. During an LDT, individuals are presented with real words (e.g., happy, knife, table) and nonwords (a string of letters that follows the orthographic rules of a language but is not a real word; e.g., blazzy, frumple, snurtle). The participant's task is to decide as quickly as possible whether the presented string of letters is a word or a nonword (Meyer & Schvaneveldt, 1971). A study conducted by Kousta et al. (2009) focused on emotional valence, testing two hypotheses: 1) a delayed disengagement hypothesis, that predicts slower reaction times for negative stimuli (Fox et al. 2001), and 2) a motivated attention and affective states model, that suggests a facilitation during processing for all affective stimuli (positive and negative; Lang et al. 1997). The study included negative (e.g., sad), positive (e.g., love), and neutral words (e.g., chair), that were controlled for various lexical and sub-lexical variables. The participants were asked to perform an LDT. The results showed that negative and positive words were recognized faster and more accurately than neutral words, with no significant differences in reaction times (RT) and accuracy between positive and negative words. The study concluded that both negative and positive words have a processing advantage over neutral words, supporting the motivated attention model. Similarly, Vinson et al. (2014) aimed to explore how emotional valence affects word recognition. They selected 1,374 words from the British Lexicon Project (BLP), a database of lexical decision times (Keuleers et al. 2012), and retrieved their valence ratings from the Affective Norms for English Words (ANEW) database (Bradley et al. 1999). In agreement with Kousta et al. (2009), the researchers found that once confounding variables are controlled, emotionally valenced words (both positive and negative) are recognized faster than neutral words.

However, the conclusions drawn from behavioral studies are not consistent, as evidenced by the variability of findings in the literature. For example, Estes and Adelman (2008), relying on a large set of words (1,011 words) from ANEW, observed that negative words produced slower RT compared to positive words. The researchers concluded that valence effects are related to automatic vigilance, defined as the preferential allocation of cognitive resources to negative stimuli (Pratto & John, 1991). In the context of psycholinguistics and lexical decision tasks, automatic vigilance is related to slower reaction times for negative words compared to neutral or positive words, because of a slower attentional withdrawal from negative stimuli.

Larsen et al. (2008) further examined the automatic vigilance hypothesis, testing the interaction between valence and arousal. Similar to Estes and Adelman (2008), their findings indicate that negative words are processed more slowly than positive words. However, the effect was not consistent across negative words. Their results highlight a complex interaction between negativity and arousal, suggesting that high-arousal negative words produce less of a slowdown during LDT than low-arousal negative words. The study revealed the complex pattern of how word valence (negativity) and arousal affect word recognition. In the same line, Hofmann et al. (2009) examined whether positive words facilitate RT due to their emotional valence independent of arousal, and whether the inconsistent findings with negative words in previous studies were due to differences in arousal levels. The words were divided into four categories: positive, neutral, low arousal negative, and high arousal negative. Again, consistent with previous studies, positive words produced significantly faster RTs in the LDT than neutral words. Similarly, high-arousal negative words elicited faster RTs than low arousal negative and neutral words. However, low arousal negative words yielded slower RTs compared to neutral words. These results suggest that arousal levels modulate the processing speed of negative words. Importantly, these studies suggest that not all negative words produce the same level of automatic vigilance.

In another study, Rodríguez-Ferreiro et al. (2019) wanted to investigate the effects of valence and arousal on word recognition in Spanish. To do so, the researchers assessed participants during an LDT and a naming task (where participants read words aloud). Similar to previous studies, the researchers found a facilitated processing for positive words. In contrast, words with negative affective content tended to delay participant responses in the LDT and, to some extent, in the naming task. On the word naming task, the effect of valence was moderated by arousal, with stronger valence effects for high arousing words. This interaction was not observed in the LDT. In general, the effect of valence was more pronounced in the LDT than in the word naming task. The authors concluded that the valence effect is more related to semantic processing.

Apart from the role of arousal, a series of studies have examined the possible interaction between valence and non-affective (lexical and semantic) variables. For instance, Kuchinke et al. (2007) focused on frequency (a measure of how frequently a word is used; Brysbaert et al. 2011) and found that for the set of high frequency words, participants were faster on positive words than on neutral or negative words, but no differences between negative and neutral words were observed. On low frequency words the results revealed faster and more accurate responses for positive and negative words compared to neutral words. The authors concluded that valence influences word recognition by a different mechanism than does frequency. In a similar study, Scott et al. (2014) found a significant interaction between valence and frequency. In line with Kuchinke et al. (2007), in the low-frequency condition, both positive and negative words elicited faster reaction times than neutral words. However, for high frequency words, positive words elicited faster reaction times than negative and neutral words, while no differences were observed between negative and neutral words.

Furthermore, Kuperman et al. (2014) conducted a large lexical decision study, involving 12,658 words and examined the role of affective variables (valence and arousal) as well as a number of lexical variables. Their results showed that, when controlling for frequency, positive words tend to be responded to more quickly than neutral words, while negative words tend to be recognized more slowly than neutral words. They also found that low arousal words tended to be recognized more quickly than high arousal words. More recently, Barriga-Paulino et al. (2022) investigated how valence effects are modulated by factors such as word frequency and arousal. The analysis revealed a significant modulation of lexical decision times by both variables. Positive words were marginally faster than negative ones. In addition, positive words were recognized faster than the neutral ones. However, negative words were slower compared to neutral ones, but only for low-frequency words. Arousal did not significantly affect word decision times.

As can be seen, despite extensive research on the processing of affective words, behavioral studies have yielded inconsistent results. This is particularly true with respect to negative valence. Overall, these studies emphasize the modulatory role of arousal, as well as the importance of controlling for various lexico-semantic variables. Indeed, word frequency (Barriga-Paulino et al. 2022; Kuchinke et al., 2007), age of acquisition (see Elsherif et al. 2023 for a review), concreteness (Barber et al. 2013; Yao et al. 2016), and imageability (Cortese et al. 2013) have been shown to influence word processing.

On the other hand, some neurocognitive research has attempted to describe the time course of the effects of affective variables (valence and arousal). For example, Hinojosa et al. (2010) investigated the processing of affective information at the early and late stages of single word processing. Early stages of single word processing were evaluated through the Early Posterior Negativity (EPN). The EPN effect, characterized by amplitude differences between emotional and neutral stimuli, reflects the automatic and fast emotion activation of the emotional content at early stages (Citron, 2012). Late stages of word processing are assessed through the late positive complex (LPC). The LPC is thought to reflect the activation and engagement of motivational circuits in the brain, particularly in response to emotionally salient stimuli (Citron, 2012). The results from Hinojosa and colleagues showed a significant EPN effect on positive words, while the analysis of the LPC also showed a significant effect of positive and negative words. The authors conclude that the affective content of word capture attention at early and late stages of word processing.

In another study, Palazova et al. (2011) explored how valence and arousal influence EPN and LPC during a LDT. In agreement with Hinojosa et al., (2010), the results of this study suggest that diverse patterns of brain activity are activated by the affective content of words during early and late processing stages (see Citron, 2012; Hinojosa et al. 2020 for a review). Similarly, in a recent study, Vieitez et al. (2021), using an LDT, explored the effects of arousal on the processing of negative words. Specifically, they focused on the EPN and LPC components. Their data suggest that unpleasant words with different levels of arousal are processed differently, with high arousal words eliciting stronger neural responses and fewer errors, and negative intermediate arousal words showing unique processing characteristics compared to neutral words. More importantly, the impact of negative valence seems to be dependent on arousal levels. They concluded that variability in arousal levels among unpleasant words can explain previous inconsistencies regarding negative valence.

In a different line of research, there has been a great interest in understanding the mechanisms by which different semantic variables influence word recognition. Previous research suggests that words which are related to several semantic features (e.g.., a large semantic neighborhood, a high number of distinct associates, a higher number of senses, etc.) are processed faster and more accurately (Yap et al. 2015). This phenomenon is known a semantic richness, and it refers to the amount and range of information associated with a word, which influences its processing (Pexman et al. 2008; Rabovsky et al. 2012; Yap et al. 2015). The influence of semantic richness during word recognition is thought to be mediated by a mechanism of semantic feedback to the lexical and letter levels. Thus, a semantically rich word generates more activity at the semantic level, which produces stronger feedback to the lexical units, speeding up the word recognition process (Pexman et al. 2008; Yap et al. 2015).

Some studies suggests that task difficulty modulates the processing dynamics during a word recognition task: as task difficulty increases, sematic feedback becomes more pronounced (O'Malley et al. 2007). In other words, as the task difficulty increases, the stronger the feedback from the semantic level to the lexical units. Variables, such as animacy (Bonin et al. 2019) and imageability (Evans et al. 2012), which have been proposed to contribute to the semantic richness of words (Muraki et al. 2020; Pexman, 2012), have been investigated with this approach. Bonin et al., (2019) examined the effects of animacy using various versions of a LDT that varied in difficulty (low, moderate, high). The authors found that words with high animacy ratings were recognized faster in the moderate and high difficulty conditions. However, no differences were reported between the moderate and high conditions. Similarly, Evans et al. (2012), examined to what extent imageability facilitates visual word recognition. The researchers developed various versions of the same LDT, each with a different level of difficulty (low, moderate, high). Their results showed that high imageability led to faster reaction times on the moderate and high difficulty tasks, but not on the low difficulty task. Moreover, the imageability effect became more pronounced as the nonwords became harder to discriminate from words. Emotional content (in particular, valence) has been proposed to be another feature of semantic richness (Pexman et al. 2008). However, this variable has not been examined yet in relation to task difficulty.

As shown by the reviewed studies, the interplay between language and emotion has generated a considerable amount of research. Many behavioral studies have consistently reported an effect of affective variables (valence and arousal) during word processing. While some studies report an advantage for positive words over negative words, others report no differences between these two. In addition, positive words are generally found to be recognized faster than neutral words, while there are inconsistent findings when comparing negative and neutral words. At the same time, interactive effects between valence and arousal have been reported. Moreover, neurocognitive research has found a differential pattern of brain responses to affective words compared to neutral words. These studies have also highlighted the importance of controlling for different lexico-semantic variables such as frequency and concreteness.

Moreover, although most studies have tried to control for several variables, the majority of them have treated affectively loaded words as a single category, without distinguishing between EM and EL words. This may have contributed to mixed findings in the literature. More recently, psycholinguistic studies have begun to rigorously explore the distinction between these two types of affective words, aiming to describe their respective differences and similarities, and examining how affective variables, such as valence and arousal, influence each word type during processing. In fact, some studies have reported processing differences between these EM and EL words. We review this research in the next section.

2.2 Emotion Words and Emotion Laden words

Several studies have investigated the differences and similarities in processing between EM and EL words, some of them with the LDT, and others, with other paradigms. For instance, Zhang et al. (2017) examined the neural response associated with the processing of EM and EL words during a LDT, by recording different ERP measures: P100, N170, and LPC. The P100 is an ERP component associated with early visual attention processes (typically peaking at 100ms) and has been observed to be larger in response to emotional words compared to neutral words, suggesting an attentional bias toward emotionally relevant stimuli (Pulvermüller, 2007; Zhang et al. 2017). Similarly, the N170 has been shown to discriminate between emotional and non-emotional stimuli (Zhang et al. 2014), with larger amplitudes in response to emotional words (both positive and negative) compared to neutral words. The results of Zhang et al. (2017) did not reveal either any emotional effect or any difference between EM and EL words in the P100 component. In contrast, a significantly larger N170 was observed in the right hemisphere for EM words in comparison to EL words, with no differences on the left hemisphere. Finally, the LPC was larger for negative words than for positive words. In addition, negative EM words elicited a larger LPC on the right hemisphere than on the left hemisphere. These results show differences in processing between EM and EL words. Specifically, the N170 and LPC data suggest that negative EM words elicit stronger affective activations.

Similar conclusions were drawn by Wang et al. (2019), who found that positive and negative EM words and negative EL words modulated both the P2 (an ERP component related to the attentional resources devoted to affective stimuli; González-Villar et al. 2014), and the N400 (a components related to semantic integration difficulty; Yao et al. 2016) during an LDT. In contrast, positive EL words only affected the N400. The authors concluded that both positive and negative EM words provide easier access to affective content, leading to earlier processing of affective information. At the same time, this difference is more pronounced for positive words (EM and EL) than for negative words (EM and EL).

Other studies have relied on different paradigms. For instance, Knickerbocker and Altarriba (2013) compared EM and EL words in a repetition blindness (RB) paradigm. In RB, participants are quickly presented with a series of stimuli in an RVSP task and are asked to detect/report any words that appear twice in the stream (Kanwisher, 1987). The results showed that EM words elicited a larger RB effect compared to EL words, demonstrating processing differences between these two types of words.

On the other hand, Zhang et al. (2019) used an emotion conflict flanker task. In this task, the target word is presented in the center of the screen, surrounded by words at top and bottom. The surrounding words may be either congruent (a positive target word surrounded by positive words) or incongruent (a positive word surrounded by negative words) in valence. The participant's task is to determine whether the target word is positive or negative (Kanske & Kotz, 2010). Zhang et al. (2019) obtained higher accuracy rates and faster RT for negative EL words than negative EM words in both incongruent and congruent conditions, while no differences were found for positive words. The behavioral results showed that negative EL words have a processing advantage over EM words. Furthermore, they recorded the N200 component, which is an early ERP component (typically peaking at 200ms) related with conflict processing, with larger amplitudes in response to incongruent trials (Kanske & Kotz, 2010). Zhang et al. (2019) observed enhanced N200 responses for negative EM words compared to negative EL words in certain conditions, whereas no differences were observed for positive EM and EL words. These results demonstrate superior conflict resolution for negative EM words.

A last groups of studies used a priming paradigm, in which the processing of a target word is affected by the previous presentation of a prime word. For instance, Kazanas and Altarriba (2015) conducted a semantic priming experiment. In this paradigm, a target word (e.g., nurse) is responded more quickly and accurately when it is preceded by a semantically related word (e.g., doctor) than when is preceded by an unrelated word (e.g., truck, Lucas, 2000). In the study of Kazanas and Altarriba (2015),word pairs were created by manipulating three variables: relatedness (related vs. unrelated), word type (emotion-label vs. emotion- laden), and valence (positive vs. negative). The researchers found that participants showed shorter RT's to related targets than to unrelated targets. Secondly, participants had faster responses to EM targets compared EL targets. They also found that positive targets had faster RT's than negative targets. Their results indicate that EM words show a greater priming effect compared to EL words, which suggests that they are processed more efficiently than EL words.

In a further study, Kazanas and Altarriba (2016) modified the previous procedure by increasing the stimulus onset asynchrony (SOA). The SOA refers to the time interval between the presentations of a prime and a target. In the study conducted by Kazanas and Altarriba (2015), the SOA was set to 250ms, a time interval that is considered as a short SOA and therefore is more likely to reflect automatic processing (i.e., there is no time for strategies). In contrast, Kazanas and Altarriba (2016) extended the SOA to 1000ms. Similar to the previous study, the researchers found a facilitation for positively valenced targets. In addition, significant priming effects were observed for both EM and EL words, with larger effects for the former. These findings support the distinction between EM and EL words.

Using a similar procedure, Wu et al. (2021) examined how affective word type (EM and EL) influences affective priming. This is a similar paradigm to semantic priming, described in the previous paragraph, but focused on affective content. Both the prime word and the target word may have a positive or a negative valence. The affective priming effect is the comparison of the time it takes participants to evaluate the target (i.e., to decide whether the word is positive or negative) in congruent (e.g., a positive prime followed by a positive target) and incongruent conditions (e.g., a positive prime followed by a negative target) (Klauer, 1997). Typically, participants are faster at judging congruent than incongruent targets. Wu and colleagues investigated whether EL targets could be primed to the same extent by EM and EL prime words. They conducted an unmasked (i.e., the prime word was visible) and a masked (i.e., the prime word was not visible and participants were not aware of its presentation) affective priming experiment and measured behavioral and electrophysiological responses (EPN and LPC). The behavioral results of the unmasked priming experiment showed that responses to EL targets were more accurate when preceded by EL primes compared to EM primes.. Interestingly, people were more accurate with negative EL primes (compared to negative EM primes), whereas positive EL and EM prime words showed similar accuracy. Lastly, larger LPC amplitudes were elicited by EL words primed by EL words compared to those primed by EM words, suggesting an easier affective evaluation of EL targets when they were preceded by words of the same type (i.e., EL words). In line with these results, in the second experiment EL targets were recognized more accurately when preceded by EL primes than when preceded by EM primes. The electrophysiological results showed an enhanced EPN for positive EL words preceded by negative EM words. In addition, the results of the LPC showed that negative word produced larger LPC amplitudes compared to positive words. In general, the results of this study show that EL target words are better recognized when preceded by EL primes than when preceded by EM primes, demonstrating that the magnitude of affective priming is larger when prime and target words are of the same type (i.e., both are EL words) than when they are of different type (i.e., EM prime words and EL target words).

Hence, several studies have shown that there are clear processing differences between EM and EL words. This phenomenon has been observed in research focusing on the study of isolated words in different tasks, such as the lexical decision task (LDT). This suggests that EL and EM words may constitute distinct categories within the lexicon. The processing differences between EM and EL words may have contributed to mixed findings in the literature. Furthermore, the behavioral and neurocognitive differences between these two types of words highlight the importance of correctly defining and studying separately EM and EL words for a comprehensive understanding of their influence in word processing (see Wu et al. 2019 for a review). On the one hand, the priming studies reviewed in this section show that EM words may be more related to each other in the lexicon than EL words, even though both are affective words. However, no study so far has addressed the organization of affective (EM and EL) words in the mental lexicon. On the other, the processing of EM and EL words needs further investigation, because of inconsistent findings. Focusing on the LDT, a topic of interest is whether emotional content (valence) behaves as a feature of semantic richness, an issue not examined in the literature. Furthermore, the influence of the EM-EL distinction on semantic richness effects has never been studied. Considering that affective content is part of the denotative meaning of EM words, but not EL words, it might be that the former are more semantically rich than the latter. These issues are the focus of this thesis, whose main goal is to understand how EM and EL words are represented and organized in our minds, and how they are processed. These objectives are addressed in three experiments. In the following section, we present in detail the general objectives of the thesis and the three studies, with their specific goals and predictions.

CHAPTER III: Aims and Outline of the Studies

3.1 General Aims

Previous studies strongly suggest that psycholinguistics research should consider two types of affective words (EM and EL words). The processing differences between EM and EL words have been extensively studied, although some inconsistencies remain. In contrast, there has been little interest in how affective words are represented and organized in the lexicon. The first objective of the present work is to study the representation of EM and EL words by 1) examining how they are organized in the mental lexicon and 2) identifying the features or characteristics that contribute most to their differentiation. The second objective is to assess whether emotional valence behaves as a characteristic of semantic richness during processing, and whether the pattern of results in relation to this differs between EM and EL words. To achieve these goals, we conducted three studies. Studies 1 and 2 are related to the first objective, and thus focus on affective words' representation and organization. Study 3 is related to the second objective and focuses on processing. Study 1 examines the associative structure of EM, EL, and neutral words. In Study 2, we created a semantic space in which EM, EL and neutral words were represented, based on variables coming from both two-dimensional emotion models and the CPM model. In this study, we also identified the most important features that define each word type. Finally, in Study 3, EM, EL and neutral words were tested in a visual word recognition task which had different levels of difficulty, to examine semantic feedback effects.

3.2 Outline of the studies

Study 1: **The contribution of affective content to cue-response correspondence in a word association task: Focus on emotion words and emotion-laden words**

The first study was designed to examine the organizational structure of EM, EL, and neutral words. We addressed this question using a word association task. This study had two main objectives. The first objective was to examine the type of associates that are produced in response to different types of cue words (EM, EL, NT). In relation to that, we assessed whether EM, EL and NT cues were likely to produce associated words of the same type. We also tested whether EM associates produced in response to EM cues have higher emotional prototypicality (i.e., are better exemplars of the category "emotion") compared to EM associates produced in response to EL or NT cues. Finally, we tested whether EL cue words produce more EM associates than NT cue words. We expected words that share affective characteristics to be connected in the mental lexicon. We also predicted EM words produced in response to EM cues to be more prototypical than EM words produced in response to other types of cues. Finally, we expected EM words to be produced as associates to a greater extent to EL cue words than NT words, indicating that EL words acquire their affective properties by their association with emotional states and events. The second objective of the study was to examine the relationship between the lexico-semantic (concreteness, frequency and age of acquisition) and affective (valence and arousal) properties of the cue words and the associated words, by examining whether these variables show assortativity. Assortativity refers to the extent to which the value of the cue word in a particular variable (e.g.., valence) predicts the value of the same variable (valence) in the associated word, to a greater extent than other features of the cue (Van Rensbergen et al. 2015). We did it considering all the cue words together and EM, EL and NT cues separately. Considering the results of previous studies, we expected valence, arousal and concreteness to display assortativity. We also expected assortativity for affective variables to be higher for affective words (EM and EL) than for neutral words.

Study 2: **What distinguishes emotion-label words from emotion-laden words? The characterization of affective meaning from a multi-componential conception of emotions**

This study was designed to create a semantic space that defines the organization of Spanish affective and neutral words. To this end, we relied not only on the affective variables proposed in the two-dimensional models of emotion (valence and arousal) (Russell, 1980), but also on variables related to the different components of the emotional response proposed in the CPM (Scherer et al. 2001). We reasoned that the inclusion of all these affective variables would allow us to better understand the differences and similarities between EM and EL words, contributing to determine which affective variables are more important in characterizing each type of word. Therefore, our first objective was to define the organizational structure of affective and neutral words in terms of their affective features. To this end, based on these affective features, we performed a Principal Component Analysis (PCA). We expected that affective features would contribute greatly to the differentiation between affective and neutral words. Furthermore, we expected affective content (in terms of valence and arousal) to be similarly relevant to EM and EL words, and therefore they might be similarly plotted in terms of these variables in the semantic space. However, we expected to be able to differentiate EM and EL words in terms of CPM variables. The second aim of the study was to determine the most relevant affective features in predicting each word type using a Random Forest Classifier (RFC). Previous studies have reported that feelings and interoception are important predictors of emotional prototypicality of EM words (Ferré et al. 2023). Based on these findings, we expected feelings and interoception to be important predictors of EM words. In addition, these variables may not be significant predictors of EL words because they do not explicitly denote an emotion. This would help us to distinguish between EM and EL words.

Study 3: **Does task difficulty increase semantic feedback? A study on the effects of valence during visual recognition of emotion- label and emotion-laden words**

The third study was designed to examine the processing of affective and neutral words. Specifically, we tested EM, EL, and NT words in a LDT with varying levels of difficulty, to examine semantic feedback effects. This study had two primary objectives. First, to examine whether valence behaves as a feature of semantic richness. Secondly, if valence behaves as a feature of semantic richness, we aimed to examine whether the effects of valence are similar or different in EM and EL words. Given that EM words directly denote emotions and were more strongly related to all the affective variables considered in the second study, we expected semantic richness effects to be more pronounced in EM words compared to EL words. To test this, we created three versions of the same LDT with different levels of difficulty (low, moderate, high). We expected valence effects to increase with increasing task difficulty. The rationale behind this is that previous studies suggest that task difficulty modulates processing dynamics during a word recognition task: As task difficulty increases, semantic feedback becomes more pronounced

(O'Malley et al. 2007). In other words, the effects of semantic feedback are more pronounced in conditions where the discriminability of words and nonwords is more difficult.

PART II

EXPERIMENTAL WORK

CHAPTER IV: Experimental Section

4.1 Study 1: The contribution of affective content to cue-response correspondence in a word association task: Focus on emotion words and emotion-laden words

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Abstract

This study aimed at examining the contribution of affective content to the organization of words in the lexicon. Based on existing free association norms and on a series of questionnaires we developed, we examined the characteristics of the words produced as associates to 840 Spanish cue words. Half of them were affective words and the other half were neutral (non-affective) words. Among the affective cue words, some words directly labeled an emotion (emotion words, EM) and others did not label an emotion, but could elicit it (emotion-laden words, EL). The words produced as associates were also classified according to this distinction. Furthermore, we examined the relationship between the lexico-semantic and affective properties of the cue words and the associated words. The results revealed that EM, EL and neutral associated words were elicited to a greater extent by cue words of the same type than by other types of cue words. Furthermore, the degree of correspondence between the affective properties of the cues and their associates was higher than that of lexico-semantic variables. These results have methodological implications for research on semantic memory and are of interest for applied studies focused on affective word organization in specific populations.

Keywords: Emotion words, emotion-laden words, word association, affective content, mental lexicon, assortativity.

1. Introduction

The interaction between language and emotion has become a topic of great interest in the last decade (see Hinojosa et al., 2020, for a review). With language, we can conceptualize, express, and elicit an emotion. Many words have an affective (emotional) content (e.g., "love", "hate", "friend", "murderer"). This emotional content is a consistent feature of language, and it can refer to internal affective states, processes, and relationships. Considering that, the substantial effort devoted in the last years to characterize the effects of emotional content on word processing is not surprising (e.g., Kuperman et al., 2014; Rodriguez-Ferreiro et al., 2019; Vinson et al., 2014). This study focuses on a much less explored issue, that is the contribution of affective content to the organization of words in the speakers' lexicon.

According to dimensional models of emotion, the affective properties of words can be characterized in terms of two basic dimensions: valence and arousal (Bradley et al., 1999; Russell, 2003; Russell et al., 1999). Valence refers to the hedonic value describing whether a word is positive or negative, and it is often assessed on an unpleasant to pleasant scale (e.g., "hate" is an unpleasant or negative word, while "love" is a pleasant or positive word). On the other hand, arousal refers to the level of activation (from low arousal to high arousal) a word conveys (i.e., the extent to which its meaning refers to something calming [e.g., "peace"] or activating [e.g., "party"]; Altarriba & Bauer, 2004; Citron et al., 2014; Russell, 1980). Therefore, by definition, affective words (i.e., words that have an emotional content) have a polarized score on the valence scale (i.e., they are perceived as highly pleasant or unpleasant). Regarding the level of arousal, there is variability among affective words, although most of them have high arousal values. On the other hand, neutral words (i.e., non-affective words, those that are neither positive nor negative) have a valence value around the middle point of the scale, and a low level of arousal (e.g., "chair," "pen"; Stadthagen-Gonzalez et al., 2017).

Neurocognitive and behavioral research has shown that valence and arousal can affect word processing. Most studies have examined whether the processing of affective words differs from that of neutral words (from which they commonly differ in both valence and arousal). These studies have found that emotional content facilitates word processing (Citron, 2012; Schacht & Sommer, 2009; Kousta et al., 2009; Yao et al., 2016). Nonetheless, this advantage is more frequently associated with positive valence (Hoffman et al., 2009). In contrast, the effect of negative valence is unclear: Some studies have reported an advantage in processing for negative words (Kousta et al., 2009), while others have reported a disadvantage (Estes & Adelman, 2008; Larsen et al., 2008) or no effects at all (Scott et al., 2014). Other studies have found that arousal alone can influence word processing, and some others have reported an interaction between valence and arousal particularly in negative valenced words (Delaney-Busch et al., 2016; Kuperman et al., 2014; see also Hinojosa et al., 2020, for a review).

Apart from having distinct valence and arousal values, affective words may also differ in their relationship with emotional content. Concretely, there is a relevant distinction between Emotion words (EM words henceforth) and Emotion-laden words (EL words henceforth). EM words directly refer to a specific emotion, that is, they denote an emotion (e.g., "love," "hate"), while EL words do not refer to an emotion but can elicit it (e.g., "party," "knife"; Altarriba, 2006; Pavlenko, 2008; Zhang et al., 2017). In other words, the affective content of EM words comes from their direct reference to an emotion, while the affective content of EL words is probably a product of the association of the word to an affective state/event. Most of the previous research in affective word processing has not taken into account this distinction, intermixing EM and EL words in their experimental materials (Chen et al., 2015; Kousta et al., 2011; Palazova et al., 2011; Yap & Seow, 2014). This may have contributed to the inconsistency of findings in the field.

Nonetheless, the distinction between EM and EL words is also relevant, considering that the few studies which have compared these two types of words have, indeed, found differences in their processing. For instance, some behavioral studies have reported a greater emotional activation, shorter response times, and larger priming effects for EM words when compared to EL words (Altarriba & Basnight-Brown, 2011; Kazanas & Altarriba, 2015). Furthermore, research involving event-related potential recording (ERP) has also reported differences between EM and EL words. Indeed, Wang et al.

(2019), found that positive EM words elicited a larger P2 amplitude than neutral words, but no effects were found in the comparison between EL and neutral words. These results indicate that emotion effects are observed earlier for EM words than for EL words. Zhang et al. (2019) also found, during conflict processing, a larger amplitude of the N200 component for both positive and negative EM words, indicating a greater early emotional activation in comparison to positive and negative EL words.

Another important distinction between EM and EL words has to do with emotional prototypicality. Emotional prototypicality is the extent to which a word refers to an emotion. Therefore, it is a unique feature of EM words. In contrast, as EL words do not describe emotions, they do not have emotional prototypicality. This unique feature has been associated with a facilitative effect during the recognition of EM words, that is, more prototypical EM words are recognized faster than less prototypical EM words (Haro et al., 2022).

Therefore, differences in processing between EM and EL words might be related to differences between these two types of words in their relationship with emotions. As suggested in the preceding paragraphs, this relationship would be more direct for EM words than for EL words. In order to address this issue, it might be helpful to examine the organization of EM and EL words in memory. As far as we know, this research question has not been addressed before. The main aim of this study was to examine the organization of EM and EL words in memory by using a free association task. In this task, participants are asked to respond as quickly as possible to a cue word with the first word that comes to his/her mind (e.g., Coronges et al., 2007; Ludueña et al., 2014; Vivas et al., 2019). The set of associates to any cue word is obtained by asking large samples of participants to perform the task. Each associated word has an associative strength value, computed as the proportion of participants who have provided that specific word in response to a cue word (De Deyne et al., 2019; Nelson et al., 2000). Associative strength indicates the connection between two words in the lexicon (De Deyne et al., 2013; Van Rensbergen et al., 2015). Consequently, free association databases provide the list of associated words elicited by a set of cue words, ordered in terms of their associative strength, with the first associated word being the one produced more frequently by the speakers.

Although word association datasets exist in various languages and some studies have described the characteristics of the cues/associates, only a few of them have considered the affective properties of words. For example, Altarriba et al. (1999) compared three types of cue words: abstract, concrete, and emotion words, finding differences between them in the number of associates produced and in their associative strength. Specifically, they observed that emotion words generated more associates, followed by abstract words and then concrete words. In addition, the first associate of concrete words showed a significantly greater associative strength than that of abstract and emotion words, without differences between the last two types of words.

In addition to the associative strength and the number of associates produced, the analysis of the characteristics of the words obtained from normative free association studies may contribute to the knowledge about the organizational structure of affective (and neutral) words in memory. Concretely, words can be characterized in terms of lexical, semantic and affective properties, such as word frequency, concreteness, age of acquisition, valence, arousal, or part of speech, among others. There is evidence that words that share some of these properties are more likely to be connected in the mental lexicon. This was demonstrated in a study by Van Rensbergen et al. (2015), who, using a large free-association dataset in Dutch, examined the extent to which each cue word and its associates display similar properties, a phenomenon called assortativity (i.e., the extent to which the value of the cue word in a particular variable predicts the value of the associated words in the same variable; Vitevitch et al., 2014). Using linear regression analyses, they found a cue-associates correspondence for valence, arousal, concreteness, and dominance, but not for word frequency, contextual diversity, and age of acquisition. These results indicated that some variables display assortativity and, therefore, are relevant in the organization of words in semantic memory. Similarly, in a study involving different languages (English, Dutch, and Spanish), Buades-Sitjar et al. (2021) analyzed the predictive capacity of three properties of cue words (valence, arousal, and concreteness) on the characteristics of their associates. The results showed that the value of the cue word in each variable was a strong predictor of the value of the associated word in the same variable. Interestingly, these three variables had been previously identified in the study by Van Rensbergen et al. (2015) as relevant properties in the organization of words in the lexicon. The studies of Van Rensberger et al. (2015) and Buades-Sitjar et al. (2021) investigated the relationship between the characteristics of the cues and their associates without distinguishing between different types of cue words (e.g., affective vs. neutral words). We made such a distinction in the present study.

The present study

This study aimed to examine the semantic organization of EM, EL and neutral (NT) words using a free association task. Our purpose was to analyze the characteristics of the words produced as associates to EM, EL, and NT cue words. We addressed this issue with a double approach. On the one hand, we analyzed the types of associated words produced for each type of cue word by classifying the associates into EM, EL, and NT words. On the other hand, we examined whether a set of affective (valence and arousal) and lexico-sematic variables (concreteness, frequency, and age of acquisition) display assortativity (i.e., a correspondence between the characteristics of the cues and the associates). This last issue was examined first by considering all the cues in general (like Buades-Sitjar et al., 2021, and Van Rensbergen et al., 2015) and then by distinguishing between the three types of cues (EM, EL and NT).

With these objectives firmly in mind, we selected 840 Spanish cue words (including EM, EL, and NT words) and identified their first three associates based on their associative strength. Most of the associates were selected from an online database of free association norms in Spanish, which contains data for 6,739 cue words (Diez et al., 2018). However, some of the selected cue words were not in the norms of Diez et al. (2018). Therefore, we carried out a word association task to collect their associates. Later we classified the associates into EM, EL, and NT words. Furthermore, we obtained the values of the cue words and their first associate in several lexico-semantic variables (valence, arousal, concreteness, age of acquisition, and frequency) to explore if they displayed assortativity.

The following research questions guided the study:

RQ1: Are words that share affective characteristics more likely to be connected in the mental lexicon and, if this is the case, is the EM-EL distinction relevant in terms of the organization of words in memory?

Hypothesis for RQ1: We expected EM words to be more consistently produced as associates to EM cues than to the other cues. Similarly, EL words would be elicited as associates to a greater extent by EL cues than by the other cues. Neutral words, in turn, were expected to be more consistently produced as associates to NT cues than to the other types of cues.

RQ2: Are EM associates elicited by EM cues more clear emotion words than EM associates elicited by the other types of cues?

Hypothesis for RQ2: We expected EM associates produced in response to EM cues to have a higher emotional prototypicality than EM associates produced in response to other (non-EM) cues.

RQ3: Do EL words acquire their affective properties through their relation to emotional states or events?

Hypothesis for RQ3: We expected EM words, which denote emotional states, to be produced as associates to a greater extent to EL cue words than to NT cue words.

RQ4: Do affective (valence and arousal) and lexico-sematic variables (concreteness, frequency, and age of acquisition) display assortativity?

Hypothesis for RQ4: Considering the results of Buades-Sitjar et al. (2021) and Van Rensbergen et al., 2015), we expected valence, arousal, and concreteness to display assortativity (that is, the values of the cues in these variables would predict the values of the associates in the same variables better than the values of the cues in any other variable). In contrast, frequency and age of acquisition would not display assortativity.

RQ5: Is assortativity for affective variables (i.e., valence and arousal) higher for EM and EL words than for neutral words?

Hypothesis for RQ5: Although we did not have a clear prediction regarding this research question, due to the exploratory nature of this analysis, it might be that assortativity for valence and arousal is greater in affective (EM and EL) words than in neutral words.

2. Methods

2.1 Materials

The stimuli consisted of 840 Spanish cue words. We assigned each cue word to one condition (EM, EL, and NT, see below). The EM and EL conditions had a total of 210 cue words each, while the NT condition consisted of 420 cue words. The EM cue words were obtained from the study of Pérez-Sánchez et al. (2021). These authors collected emotional prototypicality ratings for 1,286 words. Using a 1-to-5 scale, the authors asked Spanish-speaking individuals to rate how strongly each word describes an emotion (1 = this word does not refer to an emotion; 5 = this word clearly refers to an emotion). We selected 210 EM words with a prototypicality score of 3 or higher (i.e., words that most Spanish speakers considered highly associated with emotions).

Further, we looked for the valence and arousal ratings of these EM cue words. Most of these ratings were retrieved from the emoFinder search engine (Fraga et al., 2018), which contains different databases (Ferré et al., 2012; Guasch et al., 2016; Hinojosa et al., 2016a; Redondo et al., 2007; Redondo et al., 2005; Stadthagen-Gonzalez et al., 2017). Twenty-three EM cue words did not have valence and arousal values in emoFinder. For this reason, we collected these ratings through questionnaires. Like in Stadthagen-Gonzalez et al. (2017), valence and arousal ratings were obtained using a 9-point rating scale. For valence, one (1) indicated that the word was highly negative/unpleasant, and nine (9) indicated that the word was highly positive/pleasant, while for arousal, one (1) indicated that the word was very calming, and nine (9) indicated that the word was very exciting. We used the valence values to classify the EM cues as positive, negative, or neutral. Following Stadthagen-Gonzalez et al. (2017), words with a valence rating <4 were classified as negative, while those with a valence rating >6 were classified as positive, and words with valence values ranging from 4 to 6 were considered as neutral. Among the 210 EM selected cue words, there were 140 negative words and 70 positive words. Moreover, we used the Stadthagen-Gonzalez et al. (2017) database to search for the remaining cue words (EL and NT words) and their values in the valence and arousal dimensions. We obtained 210 EL words (distributed in the same manner as the EM words; 140 negative words and 70 positive words) and 420 neutral words.

Additionally, we collected data for several psycholinguistic properties of the cue words using emoFinder (Fraga et al., 2018) and EsPal (Duchon et al., 2013). Specifically, we obtained values for concreteness (Duchon et al., 2013; Ferré et al., 2012; Guasch et al., 2016; Hinojosa et al., 2016a, Pérez-Sánchez et al., 2021), age of acquisition (Alonso et al., 2015; Hinojosa et al., 2016b; Pérez-Sánchez et al., 2021), and word frequency measured as Zipf (Duchon et al., 2013). Comparisons between the affective (EM and EL) and neutral cue words showed differences in valence, $t(451) = 9.35$, $p < .001$, and arousal $t(579) = 21.03$, $p < .001$, while the EM and EL cue words were matched in both variables. The affective and psycholinguistic properties of the cue words are represented in Table 1.

2.2 Procedure

The associates for most cue words were obtained from the free association norms of Diez et al. (2018). However, 67 EM cue words were not in the norms (note that the EM cue words came from the emotion prototypicality study of Pérez-Sánchez et al., 2021). Therefore, we collected the associates for these cue words through questionnaires. We also included a set of filler cue words. The reason was to use a procedure as similar as possible to that described by Diez et al., (2018). In that study, participants produced associates to cue words which were not distinguished by their affective properties (i.e., there could be EM, EL, and NT words among these cues). Moreover, a free association task involving only EM cues could be perceived as strange by participants, potentially leading to response biases.

Table 1. Characteristics of affective, neutral, EM and EL cue words.

Type of cue	**Valence**	**Arousal**	**Concreteness**	**Age of acquisition**	**Zipf**
Affective	4.16 (±2.39)	6.21 (±1.23)	4.38 (±0.80)	8.02 (±1.77)	3.75 (±0.74)
Neutral	5.28 (±0.47)	4.82 (±0.55)	4.41 (±0.99)	7.98 (±1.75)	3.78 (±0.71)
EM	4.16 (±2.39)	6.21 (±1.43)	4.11 (±0.54)	8.24 (±1.63)	3.62 (±0.79)
EL	4.16 (±2.40)	6.21 (±0.99)	4.67 (±0.91)	7.79 (±1.88)	3.89 (±0.65)

Note. All values are means and SD (±). Valence scale = 1-9; arousal scale = 1-9; concreteness scale = 1-7; age of acquisition scale = 1-11 (numbers indicate the age of acquisition: 1 = under 2 years old; 2 to 10 = 2 to 10 years old; 11 = 11 years old or older).

Consequently, we constructed a series of questionnaires. The proportion of each type of cue was the same in all questionnaires: 50% EM cue words, 25% EL cue words, and 25% NT cue words. The questionnaires were responded by a total of 142 participants (mean = 41.73 per questionnaire; min = 30, max = 46); 117 females (82.39%), and 25 males, (17.61%); whose mean age was 22.7 years (SD = 6.87). Each participant answered between 1 and 4 questionnaires. The questionnaires were completed online, and participants were instructed to read each cue word and answer with the first word that came to mind. There were 11 cues on each page. Participants were asked to answer each cue, although they could indicate that they did not know the word if that was the case. The cues were randomized for each participant, and they did not have a time limit by which to submit their responses.

3. Results

3.1 Data preprocessing

After collecting the associates, the data was normalized in several steps. Firstly, we removed capital letters (e.g., "Amor" -> "amor") and corrected any special characters entered by the participants (e.g., "canciòn" -> "canción"). Plural responses to the same cue were collapsed with non-plural responses (e.g., "sentimientos" -> "sentimiento"), and any typographical error was corrected when the provided word was clear enough to be correctly interpreted. (e.g., "asquerodo" -> "asqueroso"). Then we computed the associative strength of each associated word, that is, the proportion of participants who produced that word in response to a particular cue word (out of the total number of participants who responded to that cue word).

We then classified the associates into EM, EL and NT words. To this end, we focused on the first three associated words. The reason was that the associates after the third position tend to have a low associative strength, indicating that a small number of participants have produced them. To identify the EM associated words, we relied on prototypicality values taken from Pérez-Sánchez et al. (2021). The associated words were considered as EM when their emotional prototypicality rating was greater or equal to three. Furthermore, to classify the rest of the associates as either EL or NT words, we relied on their valence ratings (using the same criteria employed to classify the cue words; see the Materials section). These ratings were taken from Stadthagen-Gonzalez et al. (2017). However, 195 associated words were not in that dataset. Hence, we constructed a series of questionnaires, following the same procedure as Stadthagen-Gonzalez et al. (2017). We created four questionnaires, which were responded by a total of 100 participants: 87 females (87%), and 13 males (13%), whose mean age was 21.68 (SD = 7.17).

Finally, to examine assortativity, we searched for the normative values of the variables to be examined in the analyses. Apart from valence and arousal, we searched for values of concreteness (Ferré et al., 2012; Guasch et al., 2016; Hinojosa et al., 2016a; Pérez-Sánchez et al., 2021), word frequency (as Zipf;

Duchon et al., 2013), and age of acquisition (Alonso et al., 2015; Hinojosa et al., 2016b; Pérez-Sánchez et al., 2021) of the first associated word. There were no normative values for 299 words in concreteness and for 14 words in age of acquisition. Therefore, we collected ratings on these variables using questionnaires. To do so, we followed the same procedure as in the datasets of reference (Ferré et al., 2012, for concreteness; Alonso et al., 2015, for age of acquisition). We elaborated 2 questionnaires with a total of 247 words each and they were responded by 97 participants: 88 females (91%), and 9 males (9%), whose mean age was 19.04 (SD = 2.55).

The file containing the cue words, the associated words, and the characteristics of both types of words are openly available in an Open Science Framework (OSF) repository at https://osf.io/c8azn/?view_only=e6bd963270764e2592afe8f8b44a47ad.

The results are divided in two parts: 1) Type of associated words produced and 2) Assortativity.

3.2 Type of associated words produced

3.2.1 Data analysis

These analyses were related to RQ1, RQ2 and RQ3 and focused on the type of associated words elicited by each type of cue word. We computed the number of EM, EL, and NT associates produced by each type of cue word and their associative strength, considering the first three associates. We also computed the mean emotional prototypicality value of the EM associates produced in response to each type of cue word. Since we had 210 EM cues, 210 EL cues, and 420 NT cues, we selected a random subgroup of 210 NT words to have the same number of items per condition in the comparison between EM, EL, and NT cues. We ran a series of one-way ANOVAs for independent measures with the type of cue word as a factor (EM, EL, NT). Post-hoc analyses were done using the Bonferroni test (in case of normal distribution) and Tamhane correction (in case of non-normal distribution). The dependent variables were the number of EM, EL and neutral words produced as associates (RQ1 and RQ3). Furthermore, we ran an independent t-test to compare the prototypicality of the EM words elicited as associates to EM cues and EL cues (RQ2). We did not include the NT cues in the analyses because they produced a very small number of associated EM words.

3.2.2 Results

The number of associated words of each type (EM, EL, and NT) produced in response to the distinct types of cue words is displayed in Table 2. Results showed a significant effect in the number of EM associates produced when comparing the three cue conditions (EM, EL, NT), $F(2,627) = 503$, $p <$

.001, $\eta p^2 = 0.62$. Post hoc analyses (T2 Tamhane) revealed differences between the three groups (all *p*s < .05), indicating that EM cues produced more EM associates than EL and NT cues. At the same time, EL cues produced significantly more EM associates than NT cues.

Table 2. Number of EM, EL, and NT (Mean and SD) associated words produced by each type of cue word.

Type of cue	Mean	SD
Mean number of EM associates		
Affective (EM & EL)	1.05	1.12
Neutral	0.03	0.19
EM	1.85	0.97
EL	0.25	0.51
NT	0.02	0.18
Mean number of EL associates		
Affective (EM & EL)	1.53	1.05
Neutral	1.38	0.93
EM	0.97	0.90
EL	2.09	0.87
NT	1.37	0.95

Mean number of NT associates		
Affective (EM & EL)	0.42	0.67
Neutral	1.59	0.93
EM	0.19	0.43
EL	0.66	0.78
NT	1.61	0.94

The analysis of the number of EL associated words produced revealed that the number of EL associates produced differed significantly between EM, EL, and NT cue words, $F(2,627) = 83.61$, $p < .001$, $\eta p^2 = 0.21$. Bonferroni post-hoc tests showed significant differences between the three groups (all *p*s < .05). Concretely, EL cue words elicited a significantly greater amount of EL associates than EM and NT cue words, while NT cue words produced more EL associates than EM cue words.

The analysis of the number of neutral associated words produced also revealed differences between EM, EL, and NT cue words, $F(2,627) = 197.32$, $p < .001$, $\eta p^2 = 0.39$. These differences were significant between all the groups (T2 Tamhane test, all *p*s < .05), indicating that NT cue words elicited more neutral associates than EM and EL cue words and that EL cue words produced more neutral associates than EM cue words.

Finally, the analysis of the prototypicality of the EM associated words elicited in response to EM and EL cue words showed a significant difference, being prototypicality higher for EM words associated to EM cues (Mean = 4.14, SD = 0.51) than for those associated to EL cues (Mean = 3.86, SD = 0.62), t (231) = 3.30, p = 0.001, d = 0.52.

3.3 Assortativity

3.3.1 Data analysis

These analyses were related to RQ4 and RQ5 and examined whether valence, arousal, concreteness, word frequency (conceptualized as Zipf) and age of acquisition display assortativity in our dataset, focusing on the cue words and their first associate. As explained in the introduction, assortativity refers to the correspondence between the cue and the associate in relation to a particular variable (e.g., to what extent the valence score of the cue word predicts the valence score of the associated word; Vitevitch et al., 2014). One way to examine this is to compare the predictive capacity of several variables of the cue on the score of the associated word in a given variable (e.g., valence). When there is assortativity, the score of the cue word in that variable (e.g., valence) better predicts the score of the associated word in that variable (i.e., valence) than the scores of the cue word in other variables (e.g., arousal, concreteness, age of acquisition, and Zipf).

We ran five linear regression models, one for each variable of the first associated word, to examine the cue-response correspondence for the variables of interest. First, we did this considering all cue words together and then with each type of cue word separately.

Following Van Rensbergen et al. (2015), we ran the analyses using the *lmg* metric in the R *relaimpo* package (Grömping, 2007). The metric *lmg* uses the R^2, which is the percentage of variation in the dependent variable explained by the variation of the independent variable. The R^2 is a measure commonly used for regression models. However, when the R^2 is used in these models, the order in which the variables are entered may affect the outcome because each order can yield different results. The *lmg* metric solves this problem by averaging across all potential orders.

3.3.2 Results

The relative contribution of each cue variable to the variance explained by the model for a particular variable of the associated word (dependent variable, DV, in the first column of the table), considering the 840 cue words and their first associate, is represented in Table 3. The proportion of variance explained by the model is also shown (last column). The significant predictors (i.e., those whose predictive capacity was significantly higher than that of all other predictors) are in bold in the table and the ones in *italic* are significantly higher than at least one of the other predictors. We tested significance by examining the overlap of bootstrapped confidence intervals included in the *lmg* metric within the R *relaimpo* package (Grömping, 2007).

Table 3. Proportion of variance of the first associated word in several variables that is explained by each variable (predictor) of the cue word (all cue words included).

Associate variables	Predictor (cues) variables					
	Valence	Arousal	Concreteness	AoA	Zipf	% Variance
Valence	**83.41%**	*13.53%*	0.74%	1.43%	0.88%	41.00%
Arousal	*19.56%*	**78.88%**	0.06%	1.16%	0.33%	33.94%
Concreteness	0.36%	3.71%	**79.66%**	*15.38%*	0.89%	15.04%
AoA	3.45%	5.27%	16.33%	**68.80%**	6.14%	13.92%
Zipf	26.84%	1.60%	4.58%	5.64%	61.35%	2.36%

Note. The “% Variance” column refers to the percentage of variance explained by the model. Values in bold are significantly different form all other predictors and values in italic are significantly different from at least one of the other predictors.

Regarding the valence of the first associate (first row in Table 3), the valence of the cue was the most significant predictor, followed by arousal, which differed significantly from concreteness, AoA and Zipf. Similarly, the arousal of the cue was the most significant predictor of the arousal of the first associate (second row), followed by the valence of the cue, which was significantly different from concreteness, age of acquisition, and Zipf. Concerning the concreteness of the first associated word (third row), the concreteness of the cue word was the most significant predictor. When we compared the other predictors, we observed that age of acquisition was significantly different from valence and Zipf but not from arousal. Therefore, the second most significant predictor of the concreteness of the associate was the age of acquisition of the cue. Regarding the age of acquisition of the associate (fourth row), the only significant predictor was the age of acquisition of the cue word. Finally, all the predictors contributed equally to the Zipf of the first associate (fifth row).

The results of the analyses conducted with each type of cue word separately (EM, EL, and NT) are represented in Tables 4, 5 and 6, respectively). The analysis restricted to EM cues revealed assortativity only for valence and arousal (see Table 4). Hence, only the valence and arousal ratings of the EM cues are significant predictors of the valence and arousal ratings of the first associated word.

Table 4. Proportion of variance of the first associated word in several variables that is explained by each variable (predictor) of the cue word (considering only EM cues).

Associate variables	Predictor (cues) variables					
	Valence	Arousal	Concreteness	AoA	Zipf	% Variance
Valence	**89.92%**	4.08%	2.36%	2.03%	1.61%	45.48%
Arousal	12.07%	**84.36%**	0.45%	2.55%	0.56%	26.04%
Concreteness	7.26%	4.33%	58.91%	14.07%	15.43%	5.20%
AoA	4.15%	29.00%	11.52%	47.29%	8.04%	5.42%
Zipf	32.95%	6.30%	7.57%	13.09%	40.07%	4.85%

Note. **Note**. The “% Variance” column refers to the percentage of variance explained by the model. Values in bold are significantly different form all other predictors.

Table 5. Proportion of variance of the first associated word in several variables that is explained by each variable (predictor) of the cue word (considering only EL cues).

Associate variables	Predictors (cues) variables					
	Valence	Arousal	Concreteness	AoA	Zipf	% Variance
Valence	**69.81%**	*22.13%*	1.42%	4.86%	1.77%	45.28%
Arousal	*20.11%*	**71.94%**	2.48%	4.69%	0.79%	31.39%
Concreteness	0.69%	0.91%	**88.83%**	6.98%	2.59%	15.83%
AoA	4.21%	0.72%	20.99%	*70.27%*	3.81%	17.84%
Zipf	2.58%	1.04%	44.69%	4.35%	47.33%	8.81%

Note. The "% Variance" column refers to the percentage of variance explained by the model. Values in bold are significantly different form all other predictors and values in italic are significantly different from at least one of the other predictors.

Table 6. Proportion of variance of the first associated word in several variables that is explained by each variable (predictor) of the cue word (considering only NT cues).

Associate variables	Predictor (cues) variables					
	Valence	Arousal	Concreteness	AoA	Zipf	% Variance
Valence	**94.98%**	3.46%	1.25%	0.21%	0.10%	8.58%
Arousal	32.42%	56.64%	3.92%	1.70%	5.32%	8.37%
Concreteness	0.13%	0.59%	*72.13%*	*25.83%*	1.33%	18.32%
AoA	11.72%	6.19%	14.36%	**62.12%**	5.61%	18.69%
Zipf	66.57%	9.62%	7.93%	5.75%	10.14%	1.90%

Note. The “% Variance” column refers to the percentage of variance explained by the model. Values in bold are significantly different form all other predictors and the values in italic are significantly different from at least one predictor.

The analysis of EL cues showed assortativity for valence, arousal and concreteness (see Table 5). The results also showed that arousal of the cue word was a good predictor of the valence of the associated word, and different from concreteness and Zipf. Regarding the arousal of the associated word, valence was a significantly better predictor than Zipf. Furthermore, the age of acquisition of the cue word predicted the age of acquisition of the first associated word significantly better than valence, arousal, and Zipf, but no differences were found between age of acquisition and concreteness.

Lastly, the analysis of the NT cues indicated that valence and age of acquisition displayed assortativity, that is, those variables of the cues were the best predictors of the same variables of the first associated word (see Table 6). Additionally, the concreteness of NT cues was a better predictor of the concreteness of the first associated word than valence, arousal, and Zipf, but their predictive capacity was not significantly different from that of age of acquisition. Age of acquisition, in turn, was a significant better predictor of concreteness than valence, arousal, and Zipf.

4. Discussion

The aim of the present work was to investigate the contribution of affective content to the associative structure of words in the lexicon. To that end, we examined the characteristics of the words produced as associates to EM, EL and NT cue words. We also examined the correspondence between several affective and lexico-semantic properties of the cue words and those of the associated words.

Our first goal was to investigate whether words that share affective characteristics are more likely to be connected in the mental lexicon, and, if this is the case, whether the EM-EL distinction is relevant in terms of the organization of words in memory. We predicted that EM, EL and NT words would be elicited as associates to a greater extent by cue words of the same type (i.e., EM, EL and NT cue words, respectively) than by the other types of cues. Our results supported this prediction. Indeed, the associates most frequently produced belonged to the same category of the cue that elicited them: EM cues produced more EM associates than EL and NT cues; EL cues produced more EL associates than EM and NT cues; NT cues produced more NT associates than EM and EL cues. We also predicted that EM associated words produced in response to EM cue words would have a higher emotional prototypicality than those elicited by EL cue words. The results supported this prediction too. Just as an example, the EM cue *desesperanza* (hopelessness) produced the EM word *tristeza* (sadness) as associate, with a prototypicality value of 4.91, while the EL cue *juego* (game) produced the EM word *diversión* (fun) as associate, with a prototypicality value of 3.05. Therefore, even though EL cue words elicited some EM words as associates, those were not considered as representative of an emotion concept as the EM associated words elicited by EM cues.

These results evidence the contribution of affective content to the associative structure of words. They are in line with the studies of Buades-Sitjar et al. (2021) and Van Rensbergen et al. (2015), who using a different approach showed the high relation between the affective properties of the cue words and those of their associates. Of note, earlier studies had concluded that participants usually generate word associates through linguistic processes, such as completion (e.g., the cue *holy* elicits *water* as associated word) and sound similarity (e.g., the cue *lumpy* elicits *bumpy* as associated word, Santos et al., 2011). Our findings, together with those of Buades-Sitjar et al. (2021) and Van Rensbergen et al. (2015) suggest that other processes come into play. Therefore, they are relevant for our understanding of semantic memory. Network-based models propose that concepts are connected to one another based on their semantic relatedness, in most cases operationalized in terms of association (see Kumar, 2021, for an overview). We have shown that affective content plays a decisive role in the establishment of these connections, a fact that should be incorporated by those models, which have not traditionally considered the affective properties of words. In this way, these results would give support to models of semantic memory which consider that sensory-motor and affective information are part of semantic representations (i.e., grounded theories, see Meteyard et al., 2012, for an overview). In addition to that, we have demonstrated that not only affective content, but also the type of affective word (i.e., EM vs EL) matters. Differences in processing between these two types of words have been reported in the literature (e.g., Altarriba & Basnight-Brown, 2011; Kazanas & Altarriba, 2015; Wang et al., 2019; Zhang et al., 2019; see also Wu & Zhang, 2020, for a review). However, the issue of their representation and their organization in the lexicon has not been addressed before. This study is the first step in this direction.

Our results also have methodological consequences. A logical prediction from network-based models is that if two words are connected, the activation of the node (the representation) corresponding to the first word would spread to the node corresponding to the other word. This is the basis of the semantic priming paradigm, which has been used extensively to investigate semantic organization and processing. In this paradigm, the processing of a target word (for example, in a lexical decision task) is facilitated by the previous presentation of a semantically related word (for reviews, see Hutchison, 2003; Lucas, 2000). Researchers commonly select the prime-target pairs based on their semantic relatedness, but they do not consider affective content. A different line of research focuses on affective priming, that is, the facilitation in the processing of a target word by the previous presentation of an affectively congruent word (see Klauer & Munsch, 2003, for an overview). In this case, researchers select the prime-target pairs based on their affective (in)congruency (e.g., positive-positive pairs vs positive-negative pairs), but the degree of associative relatedness between the two words is not always considered (see, however, Hu & Liu, 2019, for a study that has tried to dissociate both types of relations). Our results suggest that this may have contributed to the inconsistencies observed in the field, just as ignoring the EM-EL distinction. Considering that EM words tend to produce EM words as associates and that EL words tend to produce EL words as associates, the presence of null findings (i.e., lack of affective priming) may be partially explained by the presence of heterogeneous pairs (i.e., pairs containing an EM prime word and an EL target word and the other way around) in the experimental set. In fact, a recent study has provided evidence in this direction, showing that EL target words are facilitated by EL prime words, but not by EM prime words (Wu et al., 2021). Further research comparing homogeneous pairs (EM-EM and EL-EL) and heterogeneous pairs (EM-EL and EL-EM) is needed to reach firm conclusions.

Another aim of our study was to investigate whether EL words acquire their affective properties through their relation to emotional states or events. If that is the case, EM words, which denote emotional states, should be produced as associates to a greater extent to EL cue words than to NT cue words, which are not affectively loaded. These were exactly the results found in our study. Just as an example, the EM word *miedo* (fear) was the first associate of both the EM cue word *fobia* (phobia) and the EL cue word *secuestro* (abduction). One consequence of the affective properties of EL words stemming from their connection to emotional events is that the specific emotion to which each EL word is connected may show individual and cultural variations. For instance, the word "party" may be associated to happiness for an extroverted person, but not for an introverted person. In contrast, the emotional content of EM words is expected to be more stable, because it is part of the core meaning of the word, not acquired through association. This may partly explain the larger facilitative effects in processing (i.e., in comparison to neutral words) for EM words with respect to EL words (see Wu & Zhang, 2020, for a review).

Another point that deserves to be mentioned in relation to the above is the asymmetry in the pattern of association observed: EL cue words produced more EM associates than NT cue words, but EM cue words did not produce more EL associates than NT cue words (in fact, the pattern is the opposite). This suggests that the connections between the two types of affective words are not entirely bi-directional. That is, the presentation of an EL word (e.g., *secuestro,* abduction) easily leads to the activation of the associated emotion (e.g., *miedo,* fear), while the presentation of an EM word (e.g., *miedo,* fear) does not lead so directly to the activation of a situation/event provoking that emotion (e.g., *secuestro,* abduction), rather to a word denoting another emotion (*temor,* dread). This asymmetry could also have contributed to the mixed findings in affective priming research because EM primes may not facilitate always EL targets even if they are affectively congruent.

Furthermore, as indicated above, NT cues elicited a higher number of EL associates than EM cues. A possible reason is that EM words constitute a more interconnected category than EL and neutral words. Although this has not been tested empirically, some data point in this direction: EM cue words seem to be the most consistent type of cues in eliciting associated words of the same category. Although this pattern was observed in the three types of cue words (i.e., there were more associated EL words in response to EL cue words than to the other cues, and the same for NT associated words), it was more consistent for EM cues. Indeed, there were more EL associated words in response to NT cue words than to EM cue words, and there were more NT associated words in response to EL cue words than to EM cue words.

Another possible reason is related to the concreteness dimension. Indeed, some examples of EL words produced as associates to NT cue words include the words *dinero* (money, produced as associate to *empresario* [businessman]) and *hambre* (hunger, produced as associate to *saciedad* [satiety]). The word *dinero* (money) has a positive valence value of 6.75, while the word *hambre* (hunger) has a negative valence value of 2.30. Although *dinero* and *hambre* have an opposite valence (i.e., a highly pleasant word and a highly unpleasant word), they are both considered highly concrete words with a value of 5.36 and 5.25, respectively, on the 1-to-7 concreteness scale. Neutral words, by definition, have a medium score on the valence scale, but tend to have high concreteness values too. On the contrary, EM words show low rating values on the concreteness scale (they tend to be more abstract). Considering that concreteness has been identified in previous studies as a relevant variable in the organization of the lexicon (Buades-Sitjar et al., 2021; Van Rensbergen et al., 2015), it may be that EL associates are produced in response to NT cues to a greater extent than in response to EM cues due to the higher correspondence in concreteness between EL words and NT words than between EL words and EM words.

In relation to the above, a final objective of our work was to examine if a series of variables (valence, arousal, concreteness, age of acquisition and frequency) display assortativity.

That is, if the value of the first associated word in each variable is better predicted by the value of the cue word in the same variable than in other variables. Considering previous findings, we expected a high cue-response correspondence between the values of valence, arousal and concreteness, but not of frequency and age of acquisition. In the analyses that included all the cue words, we found assortativity for valence, arousal, concreteness, and age of acquisition. In contrast, word frequency did not display assortativity. These results are similar to those reported by Buades-Sitjar et al. (2021), who obtained a high correspondence between the cue words and the associated words in terms of valence, arousal and concreteness. Our findings are also in line with those of Van Rensbergen et al. (2015), who found assortativity for the same variables. These findings suggest that some variables have a decisive role in the organization of words in the lexicon. In our study, valence and arousal showed the greatest predictive capacity. Indeed, as can be seen in Table 3, the valence model explained 41% of the total variance. Within this model, 83.41% of the variance was explained by the valence of the cue. Similarly, the arousal model explained 33.94% of the total variance. Within this model, 78.88% of the variance was explained by the arousal of the cue. Apart from that, we found that the cue values in concreteness and age of acquisition are good predictors of the values of the first associate in those variables. Specifically, within the concreteness model, 79.66% of the variance was explained by the concreteness of the cue. Similarly, within the age of acquisition model, 68.80% of the variance was explained by the age of acquisition of the cue. Although these are high values, it should be noted that, overall, both models explained only a small percentage of the total variance (15.04% in the case of concreteness and 13.92% in the case of age of acquisition), compared to the total variance explained by valence and arousal models (41% and 33.94%, respectively). Therefore, although AoA displayed assortativity here, in contrast with the study of Van Rensbergen et al. (2015), the explanatory power of that variable, considering the total variance explained by the model, is very small.

A last aim of our study was to examine if assortativity for affective variables is higher for EM and EL words than for neutral words. Although we did not have a specific prediction due to the exploratory nature of these analyses, we might expect affective variables (valence and arousal) to be more relevant than lexico-semantic variables in the cue-response correspondence of affective words (EM and EL). The opposite pattern might be expected for neutral words. The analyses of the EM cues showed that valence and arousal exhibited a very strong assortativity, while no effects were observed for the other (lexico-semantic) variables (see Table 4). In contrast, both affective (valence and arousal) and lexico-semantic variables (concreteness) exhibited assortativity in the analyses focused on EL cue words (see Table 5). Similarly, the analysis of the NT cues revealed that AoA and valence displayed assortativity and that the concreteness and AoA of the cue were the best predictors of the concreteness of the first associated word (see Table 6). Taking into account these results, three aspects need to be noted. Firstly, affective content seems to be the most relevant variable in the organization of EM words (i.e., only valence and arousal displayed assortativity in the analyses focused on EM cue words). Secondly, apart from valence and arousal, concreteness seems to play an important role in the cue-response correspondence of EL words. Lastly, valence is the only variable that shows assortativity in the three types of cue words. Thus, affective content plays a very relevant role in the organization of the lexicon for both affective and neutral words and appears to be more important than lexico-semantic variables for both EM and EL words. A methodological implication of these results has to do with the procedure used to characterize words in terms of affective and semantic variables. The traditional approach has been asking large groups of participants to provide subjective ratings for large sets of words (e.g., Guasch et al., 2016; Warriner et al., 2013), which is a very time-consuming method. In a pioneering study, Van Rensbergen et al. (2016) extrapolated the emotional values of a large set of words from the values of their associated words, finding a very high correlation between the ratings estimated by this method and those obtained from human participants. Our findings, regarding assortativity, support this approach and go one step further, suggesting that it may be a particularly suitable strategy when EM and EL words are involved. The reason is that in these cases the correspondence between the affective properties of the cue words and the associates is higher.

To conclude, this study has two key findings. The first one is that affective content is very relevant in the organization of the lexicon. The second one is that not only affective content matters, but also the type of affective word (EM-EL). These findings have theoretical implications, suggesting that models of semantic memory should incorporate affective content. They also have methodological implications, suggesting that affective variables need to be considered when designing semantic priming experiments and that the associative relatedness, as well the EM-EL distinction, need to be considered when designing affective priming experiments. Another methodological implication is that the values of words regarding affective variables (i.e., valence and arousal) may be predicted from the values of their associates, especially when they are EM and EL words. These results are also of interest for applied studies focused on the processing and organization of affective words in specific populations, like old adults, or in pathologies like dementia, schizophrenia or autism, among others. Studies in the field have not traditionally distinguished between EM and EL words. Further research should be conducted to establish whether the deficit in emotional word processing observed in some of these populations (e.g., Rossell et al., 2000; Wong et al., 2022) is general or restricted to one type of affective word (i.e., EM or EL). More work is needed as well to examine whether EM words are a special class of words and whether they are more interconnected in the lexicon than other words. This study is a first step in this line.

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4.2 Study 2: What distinguishes emotion-label words from emotion-laden words? The characterization of affective meaning from a multi-componential conception of emotions

Betancourt, Á. A., Guasch, M., & Ferré, P. (2024). What distinguishes emotion-label words from emotion-laden words? The characterization of affective meaning from a multi-componential conception of emotions. *Frontiers in Psychology*, 15, 1308421. doi:10.3389/fpsyg.2024.1308421

Abstract

Past research that distinguishes between affective and neutral words has predominantly relied on two-dimensional models of emotion focused on valence and arousal. However, these two dimensions cannot differentiate between emotion-label words (e.g., fear) and emotion-laden words (e.g., death). In the current study, we aimed to determine the unique affective characteristics that differentiate emotion-label, emotion-laden, and neutral words. Therefore, apart from valence and arousal, we considered different affective features of multi-componential models of emotion: action, assessment, expression, feeling, and interoception. The study materials included 800 Spanish words (104 emotion-label words, 340 emotion-laden words, and 356 neutral words). To examine the differences between each word type, we carried out a Principal Component Analysis and a Random Forest Classifier technique. Our results indicate that these words are characterized more precisely when the two-dimensional approach is combined with multi-componential models. Specifically, our analyses revealed that feeling, interoception and valence are key features in accurately differentiating between emotion-label, emotion-laden, and neutral words.

Key words: emotion-label words, emotion-laden words, multi-componential models, random forest, action, assessment, expression, feeling, interoception.

Introduction

Language contains words that can effectively describe or elicit emotions (i.e., affective words) and words that do not evoke any emotional response (i.e., neutral words). Some researchers argue that affective information plays an important role in how we represent and process words in our minds (Citron, 2012; Kousta et al., 2011). In fact, various studies have demonstrated that affective words have a processing advantage compared to neutral words (hereinafter NT words) (Citron, 2012; Kousta et al., 2009; Vinson et al., 2014). Affective words are not a homogeneous set. We need to distinguish between two types: emotion-label words (hereinafter EM words) and emotion-laden words (hereinafter EL words) (Pavlenko, 2008). EM words explicitly indicate affective states (e.g., joy, anger). In contrast, EL words may elicit an emotion but do not express an emotion directly (e.g., murderer, birthday).

The affective content of words is usually characterized in terms of valence and arousal. Valence refers to the extent to which a stimulus is pleasant or unpleasant (e.g., "fear" is an unpleasant/negative EM word and "murder" is an unpleasant/negative EL word, whereas "joy" is a pleasant/positive EM word and "mother" is a pleasant/positive EL word). Arousal is related to the physiological state and refers to the level of activation (excitement/calmness) provoked by a stimulus (e.g., "tense" is a highly arousing EM word and "war" is a highly arousing EL word, while "relax" is a low arousing EM word and "bed" is a low arousing EL word). These two dimensions (often referred to as "core affect") are central to the understanding of human emotions (Barrett & Russell, 1999; Russell, 2003). Affective words (EM and EL) differ from NT words in both dimensions. Considering valence, affective words are perceived as highly pleasant or unpleasant, while NT words are neither positive nor negative. In terms of arousal, affective words are perceived as more arousing than NT words; however, the degree of arousal they elicit can vary.

The effects of valence and arousal during word processing have been widely demonstrated, both with behavioral (reaction times, RT) and electrophysiological (event-related potentials, ERPs) measures (see Hinojosa et al., 2020a for a review); however, the findings across different studies have not always been consistent. Studies focused on the effects of arousal during lexical decision and naming tasks have reported mixed results. For instance, Recio et al. (2014) observed slower RTs for low-arousing words, while other studies have found no arousal effects (e.g., Yao et al., 2016). Several studies on valence have reported a faster RT for positive words compared to negative words and NT words (Estes & Adelman, 2008; Hofmann et al., 2009; Kousta et al., 2009; Kuperman et al., 2014; Vinson et al., 2014; Yap & Seow, 2014). However, the effect of negative valence is unclear. Some studies have shown that negative words have a disadvantage in processing (Larsen et al., 2008), others have observed a facilitation (Kousta et al., 2009; Vinson et al., 2014), while others have reported no effect (Larsen et al., 2006; Scott et al., 2014).

The above-mentioned inconsistencies may be partly due to the characteristics of the experimental stimuli. For instance, previous studies have mixed EM and EL words in their experimental lists (Chen et al., 2015; Kissler et al., 2009; Kousta et al., 2011; Palazova et al., 2011). Nonetheless, there is behavioral and neurolinguistic evidence of the differences in processing between these two types of words (Altarriba & Basnight-Brown, 2011; Kazanas & Altarriba, 2016a; Knickerbocker & Altarriba, 2013; see Wu & Zhang, 2020, for a review). The distinction between EM and EL words has been studied in paradigms and tasks such as the affective Simon task (Altarriba & Basnight-Brown, 2011), rapid serial visual presentation (RSVP) paradigm (Knickerbocker & Altarriba, 2013), masked and unmasked priming paradigm (Kazanas & Altarriba, 2015), and lexical decision tasks (Kazanas & Altarriba, 2016b; Martin & Altarriba, 2017). These studies suggest that EM and EL words have distinct patterns of processing. For instance, it has been found that EM words yield faster RTs than EL word (Kazanas & Altarriba, 2016b). In addition, ERP studies have also shown significant differences between EM and EL words. For example, Zhang et al. (2017) found that EM words and EL words evoke distinct cortical responses at different stages of word processing. Their study found that the amplitude of the N170, a component which is sensitive to the distinction between affective and non-affective information, was larger for EM words than for EL words. This result indicates that EM and EL words are differently processed at early stages of processing. However, the analysis of the

LPC, a component which is sensitive to the positivity or negativity of a word, showed that negative EM words elicited a larger response in the right hemisphere when compared to positive EM words and to EL words. These findings imply that the neural correlates and hemispheric processing of EM and EL words are different.

Similarly, a more recent study compared EM and EL words in an affective priming paradigm (Wu et al., 2021). This paradigm makes it possible to examine how the presentation of a (prime) word affects the processing of a (target) word presented immediately after. The typical result is a facilitative effect in congruent trials, where both the prime and the target share the same affective polarity (e.g., a prime word with a positive valence and a target word with a positive valence), compared to incongruent trials, in which the prime and target have different affective polarities (e.g., a prime word with positive valence and a target word with negative valence; Klauer, 1997). In the study conducted by Wu et al. (2021), all the targets were EL words, while the primes could be either EM or EL words. A main finding of this study was that EL targets were processed more accurately when they were primed by EL words rather than by EM words.

The study of Wu et al. (2021) shows that, despite the affective congruency/incongruency between the prime and the target, the type of word (i.e., EM vs. EL) also determines affective priming. This suggests that there may be differences in affective content between these two types of words. As mentioned earlier, EM words have inherent affective properties because they refer directly to an affective state. In contrast, the affective content of EL words probably comes from their association with personal experiences (Wu & Zhang, 2020). Betancourt et al. (in press) obtained some evidence of this. These authors examined the associative structure of EM, EL, and NT words using a word association task. In this task, participants are asked to quickly respond to a cue word with the first word that comes to their mind (i.e., an associated word). The authors found that EM cues produced a higher number of EM associates in comparison to EL cues. Importantly, EL cues produced a greater amount of EM associates than NT cues. These results suggest that EM words are strongly connected in the mental lexicon and that the affective content of EL words is acquired by association to affective states.

As previously mentioned, affective content has generally been studied in terms of valence and arousal (e.g., Bradley et al., 1999; Barrett & Russell, 1999; Russell, 2003). However, these two variables are not sufficient to differentiate between EM and EL words. On the one hand, both EM and EL words are either positive or negative and tend to be more arousing than neutral words. On the other, the literature reviewed shows that, despite being matched in terms of valence and arousal, EM and EL words behave differently in several experimental paradigms. Therefore, further analysis is needed for an accurate distinction between these two types of words. In this study, we aim to describe the affective content of EM and EL words by examining a set of features, other than valence and arousal, that are related to the emotional experience.

Some theorists suggest that the emotional experience is shaped by multiple factors. Of interest here is the Component Process Model (CPM) of emotion proposed by Scherer and co-workers (Sander et al., 2018; Scherer, 2009; Scherer, 2001), which describes emotions as a complex and dynamic process that involves different response mechanisms. The model identifies five components: 1) cognitive appraisal (*assessment*), 2) physiological activation (*interoception*), 3) motor expression (*expression*), 4) action tendencies (*action*), and 5) subjective feeling (*feeling*; Sander et al., 2018; Scherer, 2009). The cognitive appraisal (hereinafter *assessment)* component involves evaluating the importance of a stimulus by considering its impact on the individual's wellbeing and survival. The physiological activation (hereinafter *interoception)* refers to detecting internal bodily changes like increased heart rate, muscle tension, or sweating. The motor expression (hereinafter *expression)* component encompasses various forms of expression, such as facial expressions, vocal expressions, body movements, gestures, and posture. The action tendencies (hereinafter *action)* component refers to a readiness to act in a certain way, related to the urge to approach or avoid something to achieve a specific goal. The subjective feeling (hereinafter *feeling*) component is shaped by an integrated awareness of the previous components, and this integration may result in anger, sadness, or other feelings that can be categorized or verbally labeled according to the semantic profile of emotion words (Scherer, 2009).

Several studies have examined how the components described by the CPM can be helpful in the characterization of EM words (Fontaine et al., 2007; Gentsch et al., 2018; Gillioz et al., 2016; Scherer & Fontaine, 2019). For example, Fontaine et al. (2007) explored the dimensional space that best accounts for the similarities and differences within EM words. Using a principal components analysis, they obtained a four-dimensional solution which included these dimensions: evaluation-pleasantness, potency-control, activation-arousal, and unpredictability. These findings were replicated in three different languages (English, French and Dutch). In a further study, Scherer and Fontaine (2019) conducted a larger-scale analysis using 142 emotion features, finding that the semantic structure of emotion words is consistent with the CPM. A similar approach was adopted by Ferré et al. (2023), who collected subjective ratings for a large set of potential EM words in relation to a series of variables associated with the different components of emotion: action, assessment, expression, feeling, and interoception. They also considered other variables, such as valence and arousal. Feeling and interoception were identified as the most relevant predictors of emotion prototypicality (i.e., the extent to which a word exemplifies an emotion). That is, words were more likely to be considered as good exemplars of the "emotion" category if they were associated greatly with feelings and internal bodily sensations (interoception). This result indicates that these two variables are crucial for defining the emotional experience.

The above-mentioned studies, which focused on EM words, highlight the importance of incorporating the variables proposed by the CPM into research on the affective content of words. The aim of this study was to examine whether the most relevant affective characteristics of EM words are also useful to differentiate EM words from EL words, and if they distinguish these two types of words from neutral words. We used the same framework as Ferré et al. (2023) and examined the role of a set of variables related to the different components of the emotional response, as well as the role of valence and arousal. Based on the findings presented in Ferré et al. (2023) we anticipated that the feeling and interception components to be important predictors of EM words. More importantly, since the feeling component is associated to the integration of various processes that culminates in the categorization of an specific emotion, we anticipate that this component will play an important role in differentiating EM and EL words. To achieve this, we collected ratings for a large set of EM, EL, and NT words in relation to assessment, interoception, expression, action, and feeling. We used a double approach with these ratings. First, we created a semantic space using a Principal Component Analysis (PCA) to provide information about the organizational structure of EM, EL and NT words. Second, we made a prediction model using a Random Forest Classifier to identify the variables that most predicted whether a word belonged to a certain type. Based on the findings of Ferré et al. (2023), we expected feeling and interception to be the most important predictors of word membership in the EM category. Furthermore, these variables might not have a significant role in the definition of EL words, considering that they do not denote emotions, and thus contribute to the differentiation between EM and EL words.

Method

Participants

Word ratings were obtained from 386 participants. The final number of valid participants after data cleaning (see below) was 370 (318 females, 85.95%, and 52 males, 14.05%), whose mean age was 19.46 (SD = 3.64). Participants were students at the Universitat Rovira i Virgili in Tarragona, Spain. Each participant completed one or more questionnaires in exchange for academic credits or as a volunteer. All participants signed an informed consent form before starting the ratings. The research was conducted in line with the APA ethical standards. Approval was granted by the Ethics Committee for Research on People, Society and the Environment of the Universitat Rovira i Virgili (CEIPSA-2021-PR-0044).

Materials

The materials for this study included 800 Spanish words from different sources. A total of 104 Spanish EM words were obtained from the Pérez-Sánchez et al. (2021) database, which contains 1,286 words rated in emotional prototypicality, that is, the degree to which a word refers to a human emotion. The selected words included nouns with a prototypicality score greater than or equal to 3 (in a scale from 1 = "this word does not refer to an emotion", to 5 = "this word clearly refers to an emotion"), and with a frequency per million score (taken from Duchon et al., 2013) of 1 or higher (see a similar criteria in Gillioz et al., 2016). The selected EM words had an average prototypicality rating of 3.73 (*SD* = 0.51). We discarded derivatives of the same word (e.g., *ilusión* [excitement] vs. *desilusión* [disappointment]; discarded word) and words with different or ambiguous meanings (e.g., *éxtasis* [ecstasy]).

The 696 additional words (EL and NT words) were taken from Stadthagen-Gonzalez et al. (2017), a database that contains 14,031 Spanish words that are rated in valence and arousal. In order to select EL and NT words, and not to include EM words by mistake, we crossed this database with that of Pérez-Sánchez et al. (2021), which only contains EM words. We removed the words in common between both datasets. This left us with only EL and NT words. Then we only included EL and NT words that had a frequency per million greater than or equal to 1 (taken from Duchon et al., 2013). We randomly selected 696 words from this pool and checked them to be sure that no word explicitly labeled an emotion. We used valence values to classify these words into EL and NT. EL words had a valence rating < 4 or > 6, indicating a negative and a positive valence, respectively. Neutral words had a valence rating $\geq$ 4 and $\leq$ 6 (Stadthagen-Gonzalez et al., 2017). The final selection included 104 EM words, 340 EL words, and 356 NT words.

Procedure

We focused on seven dimensions: valence, arousal, action, assessment, expression, feeling, and interoception. The ratings for valence and arousal were taken from Stadthagen-Gonzalez et al. (2017). The ratings for the CPM variables (action, assessment, expression, feeling, and interoception) were obtained through a series of questionnaires which were created and administered online using TestMaker (Haro, 2012). The questionnaires for each variable were divided into five versions. Each version contained the same set of randomly assigned words for the five variables. We ended up with 25 questionnaires with 160 words per questionnaire (eight pages each with 20 words per page). The order of presentation of the words was randomized for each participant. None of the participants who completed more than one questionnaire repeated the same set of words and variables. Participants were instructed to rate each word using a 1-to-7 scale (see Table 1 for instructions).

Each questionnaire had an option to indicate that the participant was not familiar with a given word ("*No conozco la palabra",* I don't know the word). The dataset used in the present study can be found in online repositories in an Open Science Framework (OSF) repository at https://osf.io/hxcm2/?view_only=74adb248fc88443fabc5ad1daa6abbc6

Results

Data cleaning and descriptive statistics

Sixteen participants were eliminated from the total pool of 386. The criteria to eliminate a participant were: 1) A high percentage of identical ratings (i.e., they rate more than 95% of the words in a questionnaire with the same score), and 2) A low correlation between the participant ratings and those of the group who filled out the same questionnaire (correlation lower than 0.1). The final number of valid participants was 370 (mean = 37.04 participants per questionnaire: min = 30, max = 47, *SD* = 4.75). The descriptive values for each variable, and for each word type are shown in Table 2.

Table 1. Instructions

Variable	Instruction	Scale (from-to)
Action	I relate this word with taking action, doing something, and influencing	1 “strongly disagree” to 7 “completely agree”
Assessment	I relate this word with situations that are important for my well-being and/or my survival	1 “strongly disagree” to 7 “completely agree”
Expression	I relate this word with alterations/changes in my body	1 “strongly disagree” to 7 “completely agree”
Feeling	I relate this word with feelings	1 “strongly disagree” to 7 “completely agree”
Interoception	I relate this word with internal bodily sensations	1 “strongly disagree” to 7 “completely agree”
Valence	I consider this word to be highly/slightly unpleasant or slightly/highly pleasant	1 “unpleasant” to 9 “pleasant”
Arousal	I consider this word to be highly/slightly calming or slightly/highly exciting	1 “calming” to 9 “exciting”

Note. Valence and arousal ratings were taken from Stadthagen-Gonzalez et al., (2017).

Table 2. Characteristics of EM, EL and NT words.

	EM	EL	NT
Action	5.04 (±0.61)	3.98 (±0.98)	3.27 (±0.93)
Assessment	4.56 (±1.15)	4.07 (±1.09)	3.37 (±0.76)
Expression	5.23 (±0.55)	3.71 (±0.87)	2.77 (±0.71)
Feeling	5.80 (±0.58)	3.65 (±1.04)	2.54 (±0.76)
Interoception	5.37 (±0.63)	3.64 (±0.89)	2.67 (±0.69)
Valence	4.61 (±2.49)	5.85 (±1.81)	5.28 (±0.50)
Arousal	6.26 (±1.47)	5.39 (±1.24)	5.07 (±0.72)

Note. All values are means and SD (±).

Reliability and validity

We assessed the interrater reliability of the measures using a split-half procedure and computing the Spearman-Brown coefficient with the participants' ratings. The average Spearman-Brown coefficient was r = .94 for action (ranging from .94 to .96), r = .94 for assessment (ranging from .92 to .95), r = .95 for expression (ranging from .93 to .95), r = .95 for interoception (ranging from .93 to .96), and r = .97 for feeling (ranging from .96 to .98).

We also examined the validity of our ratings by comparing the ratings collected in the questionaries with those reported in previous normative studies. This was based on the 103 words that overlapped with the study of Ferré et al.

(2023). We found moderate to high Pearson correlations for all the variables: action: $r(101) = .49$, $p < .01$; assessment: $r(101) = .92$, $p < .01$; expression: $r(101) = .55$, $p < .01$; feeling: $r(101) = .54$, $p < .01$; and interoception: $r(101) = .40$, $p < .01$).

PCA analysis, feature distribution and semantic space

Principal Component Analysis (PCA) is a statistical procedure that helps to reduce dimensionality (i.e., the total number of features in a dataset) while retaining the highest amount of information (Jolliffe & Cadima, 2016). Dimensionality is reduced by transforming the data into a new set of variables called principal components. The assembly of each component is typically based on a correlation matrix which measures the relationship between each feature within the dataset. PCA helps to determine whether samples can be grouped by assessing similarities and differences between them. Observations are generally represented using a coordinate system that makes it possible to identify each observation in a two-dimensional space (Jolliffe, 2002). We reduced dimensionality using a PCA with varimax rotation and Kaiser normalization using SPSS (version 29) and XLSTAT (Addinsoft, 2023). A correlation matrix (see Table 3) was used as the input format for the PCA. Our data obtained a Kaiser-Mayer-Olkin (measure of sampling adequacy) index value of .829, which indicates that the correlation matrix is adequate for the analysis. Components with eigenvalues below 1.0 or which accounted for less than 10% of the variance were not considered when the number of components was selected. We ended up with a solution containing two principal components (see Table 4). Principal Component 1 (PC1) explained a total variance of 59.69%, while Principal Component 2 explained a total variance of 25.04%, with a cumulative proportion of explained variance of 84.73% after varimax rotation.

Table 4 shows the outcomes of performing a PCA across all the variables with the varimax rotation. PC1, which explains most of the model variance (59.69%), is formed by interoception, expression, assessment, feeling, and action. PC2, which accounts for 25.04% of the total variability, is formed by valence and arousal. Furthermore, although assessment did not constitute a component of PC2, it still had a considerable load in that factor.

PC1 accounts for most of the variability in the dataset, and it is mainly constructed with the CPM variables. The variables within PC1 exhibited positive loadings, indicating that all of them are positively correlated. In other words, the features that make up PC1 share a common underlying component that causes them to increase or decrease together. The positive correlation between these features can be observed in Figure 1, in which they are plotted on the right side of the figure.

Table 3. Correlation Matrix (Pearson coefficients).

Variables	Interoception	Expression	Assessment	Feeling	Action	Valence	Arousal
Interoception		**.90**	**.68**	**.89**	**.77**	.06	**.33**
Expression	**.90**		**.64**	**.89**	**.78**	-.01	**.40**
Assessment	**.68**	**.64**		**.59**	**.67**	**.51**	-.06
Feeling	**.89**	**.89**	**.59**		**.78**	-.02	**.35**
Action	**.77**	**.78**	**.67**	**.78**		**.07**	**.35**
Valence	.06	-.01	**.51**	-.02	**.07**		**-.53**
Arousal	**.33**	**.40**	-.06	**.35**	**.36**	**-.53**	

Note. Values displayed in bold are significant at an alpha level of .05.

Table 4. Variable loadings after Varimax rotation.

Variables	PC1	PC2
Interoception	**.945**	
Expression	**.941**	
Assessment	**.780**	.496
Feeling	**.925**	-.137
Action	**.892**	
Valence	.127	**.910**
Arousal	.350	**-.799**

Note. Loadings smaller than .10 are not shown. Variables were included in a component if they had values equal to or greater than .5. Values in bold indicate the variables which belong to each component.

PC2 accounts for a smaller amount of variance. PC2 has a positive loading for valence and a negative loading for arousal, which means that the variables in this component tend to move in opposite directions. In fact, when we analyzed the correlation coefficients between the features within each Principal Component, valence and arousal exhibited a negative correlation (-.525). The sign difference in PC2 loadings is visible in Figure 1, in which valence is projected at the top of the figure while arousal is projected at the bottom.

We used the component scores after varimax rotation as a coordinate system to represent the distribution of each word in a two-dimensional space (see Figure 2). As shown in Figure 2, NT words are primarily projected to the left-center side of the figure, while EM words tend to be projected to the right upper and lower side. On the contrary, EL words are distributed across the entire figure with a tendency to be on the upper and lower sides. Figure 2 suggests that NT words tend to show a low score for the CPM variables and show average valence and arousal values. EM and EL words have a similar relationship with PC2, by exhibiting a polarized projection towards the upper or lower part of the figure. However, there is a clear distributional distinction in terms of PC1. As Figure 2 shows, the distribution of EM words (e.g., love, sadness) exhibits a closer proximity to the PC1 variables with respect to both EL and NT words, meaning that EM words tend to show a high score for the CPM variables. At the same time, EL words are plotted more closely to the PC1 variables than NT words, which indicates that EL words tend to have a higher score for the CPM variables than NT words.

Figure 1. Feature projection after varimax rotation.

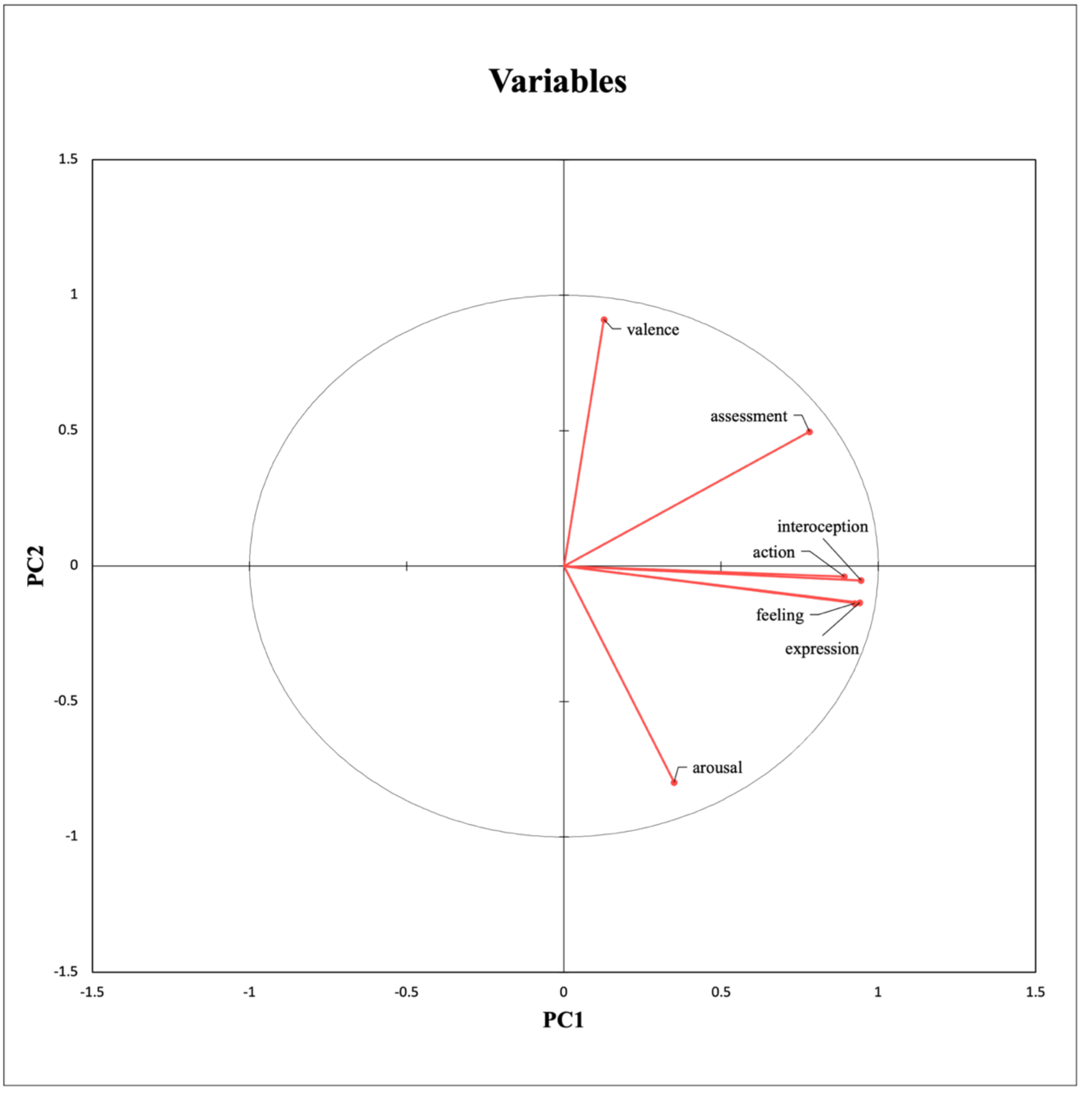
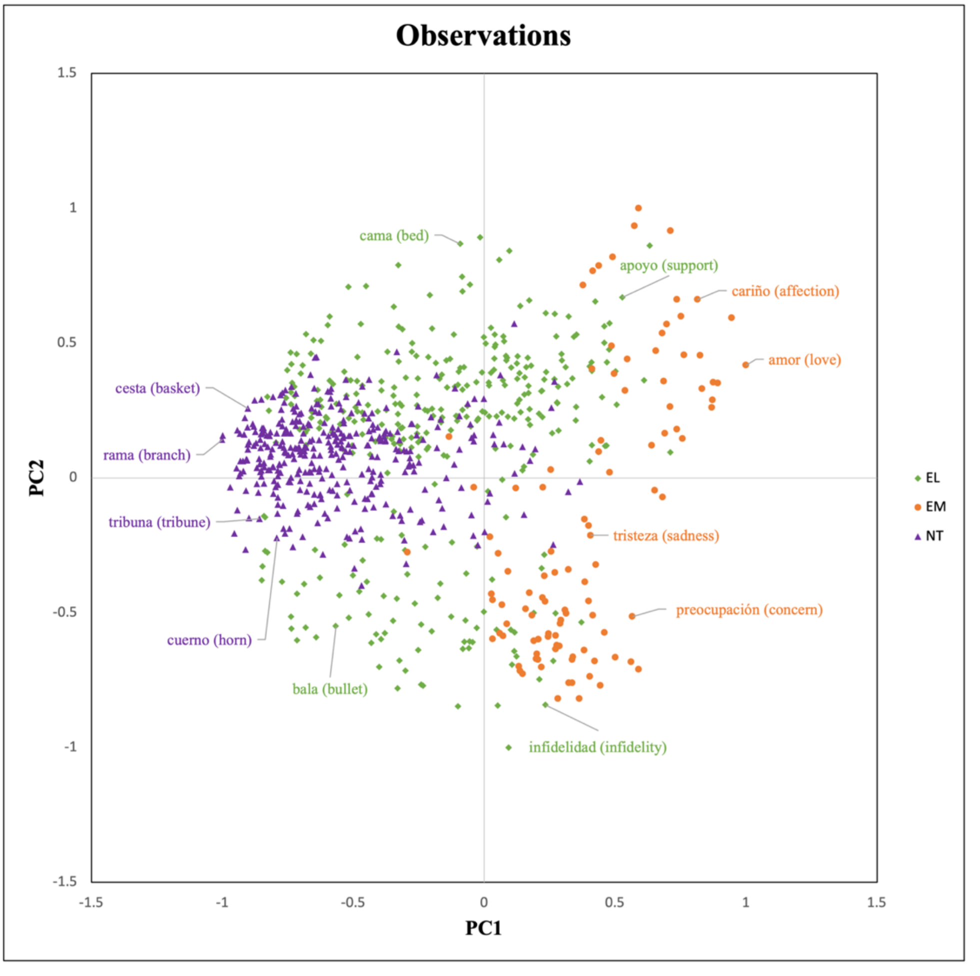


Figure 2. Words projection after varimax rotation.



Random Forest Classifier

PCA is a useful dimension reduction tool that provides information about the distribution of EM, EL and NT words in a coordinate system in relation to various features. However, it does not directly capture each individual variable's contribution to the characterization of a particular class of words. The Random Forest Classifier is a useful technique to address this issue. It enables us to determine the impact of each feature on the prediction of whether each particular word belongs to the EM, EL, or NT types (see the Appendix for a detailed explanation of this method).

We included the 800 words of the study in the analysis. Using Python version 3.7.2 and Scikit-learn library (Pedregosa et al., 2011), we created a prediction model using Random Forest Classifier (RFC) with Recursive Feature Elimination (RFE). The model used a total of 10,000 decision trees, had a maximum depth of 7, and a maximum number of features equal to the square root of the total number of features ($\sqrt{7}$). In addition, we adopted a train-test-split ratio of 75% for training (the portion of the dataset that is employed to train the model) and 25% for testing (the portion of the dataset that is used to test the prediction of the trained model). Before splitting the data into the training and the test datasets, we established a "*random state*", which controls the randomization of the data so it is reproducible. We created a code that iterates over 200 possible random states to later use the average predictive accuracy of the 200 models. The results showed that the lowest predictive accuracy was 91.5%, the maximum was 98.5%, and the average accuracy of the 200 models was 95.7%. Within the 200 models, no random state reproduced an accuracy of precisely 95.7%. Therefore, we selected the nearest highest model, which had an accuracy of 96%. Therefore, after training the RFC, our final selected model predicted the classes of the unseen dataset (testing data) with 96% accuracy.

We conducted an in-depth analysis to determine the most relevant features for predicting each word class independently (EM, EL, and NT). Feature importance was calculated using the prediction accuracy. We used the Mean Decrease in Accuracy (MDA) for this analysis. MDA is an approach that calculates the increase in error resulting from the performance of the model with and without a feature (Petkovic et al., 2018). This procedure is carried out for all decision trees and features, providing an estimate of the effect of each feature on the accuracy of class prediction. In the context of MDA, a positive contribution from a feature indicates that including it enhances the prediction accuracy for that class. Conversely, a negative contribution implies that a particular variable does not provide additional information, thus decreasing the overall accuracy. The results are shown in Table 5. All the features positively contributed to predicting EM words. The feature that contributed the most was feeling, while action and valence contributed the least. The feature that contributed the most to predicting EL words was valence, while feelings, interoception, and arousal made negative contributions. That is, excluding feelings, interoception, and arousal increases the predictive accuracy for EL words. Finally, valence was the feature that contributed most to predicting NT words. In contrast, the remaining features made negative contributions, indicating that adding these features reduces the model's ability to correctly identify NT words.

Table 5. Mean Decrease in Accuracy per class.

	EM	EL	NT
Action	9.79%	0.55%	**4.0%**
Assessment	16.69%	0.55%	**4.0%**
Arousal	13.24%	**0.59%**	**4.0%**
Expression	16.69%	1.68%	**4.0%**
Feeling	23.59%	**0.59%**	**2.80%**
Interoception	16.69%	**1.73%**	**4.0%**
Valence	9.79%	28.95%	12.87%

Note. Each value refers to the accuracy impact of each individual variable. Values in bold negatively impact the class prediction.

Discussion

Numerous studies on differentiating between affective and neutral words have focused exclusively on a two-dimensional model that relies on valence and arousal. These two dimensions cannot explain the differences between EM and EL words. The main objective of the present study was to identify the distinctive affective features of EM, EL, and NT words. We collected word ratings of various variables related to the different components of the emotional response, according to multi-componential conceptions of emotion (the Component Process Model, CPM). These variables are action, assessment, expression, feeling, and interoception. Then, we carried out a Principal Component Analysis (PCA) and a Random Forest Classifier (RFC) technique based on the ratings of the words in these variables as well as in valence and arousal. The results showed that feeling, interoception and valence are key features for accurately differentiating between EM, EL and NT words.

The PCA yielded a two-dimensional solution with two principal components. PC2 accounts for the least amount of variability and is composed of valence and arousal, with valence being the feature that contributes the most to the explained variability. This factor distinguishes affective (EM and EL) words from neutral words: NT words are characterized by mid-value scores in valence and arousal, while EM and EL words display more extreme values. This result indicates that EM and EL words are associated with a positive or negative emotion and with varying levels of activation, while NT words are not associated with a positive or negative emotion, and they do not elicit strong levels of activation. The relevance of these variables in the clustering of affective and neutral words is in line with two-dimensional models (Russell, 2003; Russell & Barrett, 1999), which have been the most popular for characterizing the affective properties of words as well as studying their influence on linguistic processing (e.g., Kuperman et al., 2014; see Hinojosa et al., 2020b, for a review).

The results of the PCA also show that more than two features are needed to account for the distribution of EM, EL, and NT words in a semantic space. Indeed, although affective and NT words can be distinguished in terms of valence and arousal, these two dimensions are not sufficient to distinguish between EM and EL words, as indicated by the relevance of the other component identified in the analysis. Principal Component 1 (PC 1) accounts for most of the variability and is characterized by the Component Process Model (CPM) variables: action, assessment, expression, feeling, and interoception (Scherer, 2001). Our results show that EM words are more closely related to CPM variables than EL and NT words. In contrast, NT words display low ratings for the CPM variables, while EL words show more variability (from low to high scores, see Figures 1 and 2). In fact, EL words are plotted in the space between NT and EM words. This finding aligns with those reported in Betancourt et al. (in press), who found that EL words produced a higher number of EM associates compared to NT words during a free association task, and therefore are more connected to emotional states than NT words.

Moreover, our findings suggest that the speakers perceive EM words as clearly related to an appraisal process that results in a certain assessment, a set of physiological changes, an expressive response, a tendency to act, and a feeling associated with a particular emotion. This highlights the multidimensionality of the states described by EM words and points towards the need to adopt an appraisal-driven componential approach to correctly characterize how we represent EM and EL words in our minds. Previous studies have distinguished between EM and EL words in terms of processing (Kazanas & Altarriba, 2015; Knickerbocker & Altarriba, 2013; Wang et al., 2019; Wu, Zhang, & Yuan, 2021); however only a few studies have been interested in their semantic representation. This work shows, for the first time, that EM and EL words have distinct representational features related to multi-componential affective responses.

This study followed the approach used by Ferré et al. (2023), who aimed to identify the features that define EM words. The authors examined the contribution of CPM variables to the emotion prototypicality of a set of potential EM words, and identified interoception and feeling as the best predictors of emotion prototypicality. This suggests that these variables are closely linked to the affective experience. The results of the PCA are in the same line. We also found that interoception and feeling are among the variables that most contribute to PC1. In particular, interoception was the variable with the highest load in this factor. Therefore, among the CPM variables, interoception and feeling are not only the best variables for characterizing EM words (Ferré et al., 2023), but also the ones that contribute most to distinguishing between EM and EL words.

In addition to describing the semantic space of EM, EL and NT words, we were also interested in the contribution that each individual feature makes to predicting each word type. To this end, we conducted an RFC and analyzed the mean decrease in accuracy (MDA). The results of this analysis indicated that EM, EL, and NT words have unique affective features. Indeed, the characteristic that mainly defines NT words is their valence. This result is not unexpected because, by definition, NT words have valence values between 4 and 6 on a scale that goes from 1 to 9 (Stadthagen-Gonzalez et al., 2017). In other words, affective words are characterized by extreme valence values, while NT words are restrained to mid-range valence values. This suggests that NT words are primarily defined by the absence of a negative or positive (pleasant/unpleasant) emotion. This finding is coherent with the results of the PCA analysis in which NT words were clearly differentiated from affective words in PC2 in terms of valence more than in terms of arousal.

The RFC results revealed that four out of the seven features examined in this study positively influenced the prediction of EL words. These features are valence, expression, action, and assessment. The MDA indicated that valence is the most important predictor of EL words. That is, the defining characteristic of EL words is their positive/negative polarity, more than their arousal. This finding is consistent with the PCA, in which we observed that valence strongly influences the distribution of EL words in the semantic space. In fact, the RFC indicates that only valence stands out as a relevant variable in predicting the three word types (EM, EL and NT words). This finding aligns with research revealing that valence is one of the most important organizing features of words in the mental lexicon (Betancourt et al., in press; Buades-sitjar et al., 2021; Van Rensbergen et al., 2015).

Apart from valence, other features such as expression, action, and assessment also emerged as influential predictors of words belonging to the EL class, although to a lesser extent. Consequently, it seems that EL words may also activate some bodily and behavioral responses by prompting individuals to evaluate and interpret the significance of a situation concerning different outcomes. However, CPM variables clearly play a greater role in predicting whether words belong to the EM class. In fact, all the affective variables considered in this study (action, arousal, assessment, expression, feeling, interoception, and valence) positively impact the prediction of EM words, and the most important variable is feeling. This is in line with the results obtained in the PCA, showing that CPM variables are determining factors in the distribution of EM words in the semantic space. This result is also in accordance with Ferré et al. (2023), who identified feeling and interoception as the best predictors of emotional prototypicality in EM words. Therefore, both the present results and those from Ferré et al. (2023) highlight feelings and internal bodily sensations as the most distinguishing features of EM words. It is noteworthy that the relevance of the last factor has been evidenced by several studies, which report that interoceptive and somatosensory processes play a major role in generating the emotional experience (e.g., Kreibig, 2010; Nummenmaa et al., 2014). Therefore, the present results suggest that the semantic content of EM and EL words is related to distinct affective features. This may contribute to the differences in emotional processing observed between these two types of words (e.g., Wang et al., 2019; Wu & Zhang, 2019; Zhang et al., 2019, 2020).

A limitation of the current study is the gender imbalance of the sample, with 86% of female participants. This is a common shortcoming of affective (e.g., Montefinesse et al., 2014; Soares et al., 2012; Stadthagen-González et al., 2017) and non-affective (e.g., Brysbaert et al., 2014; Hinojosa et al., 2021) rating studies. However, cross-gender correlations tend to be very high, indicating a high consistency between women's and men's affective ratings (e.g., Montefinese et al., 2014; Redondo et al., 2007; Soares et al., 2012). Despite this, future research should include a more balanced distribution to examine in depth the possible differences between genders and increase the generalizability and ecological validity of the findings. On the other hand, future studies may be conducted to investigate the role of other, non-affective variables, on the distinction between EM and EL words. Both age of acquisition (Pérez-Sánchez et al., 2021; Wu, 2023) and sensory experience (Wu, 2023) are worth to be considered, because they are related with the emotional prototypicality of EM words.

To sum up, the present study confirms that valence is a crucial variable in the organization of the mental lexicon, as it distinguishes affective from neutral words. It also shows that other variables related to the multi-componential experience of emotion need to be considered to differentiate EM and EL words. Among these, feeling and interoception seem to be the most relevant. More importantly, EM words seems to be related to a more complex and dynamic emotion process which is related to different components, culminating in the categorization (or labeling) of an emotion episode. On the contrary, EL words seem to be related to a very early appraisal process in which we evaluate how pleasant or unpleasant (negative or positive) a word is. Overall, these findings demonstrate the importance of combining two-dimensional models with multi-componential models of emotion to provide a comprehensive understanding of the human affective space.

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APPENDIX

Random Forest

Breiman (2001a) developed the Random Forest (RF) algorithm as an extension of decision trees. RF is a powerful machine learning algorithm used for classification and regression problems. The RF is an ensemble method, which is a technique that typically combines the predictions of hundreds of decision trees. A decision tree is assembled based on a training dataset (Rokach & Maimon, 2005). It is a tree-like structure that divides the input data into different subsets according to the values of various features or dimensions. The decision tree structure consists of a root node, a decision node, and a leaf node (see Figure 1).

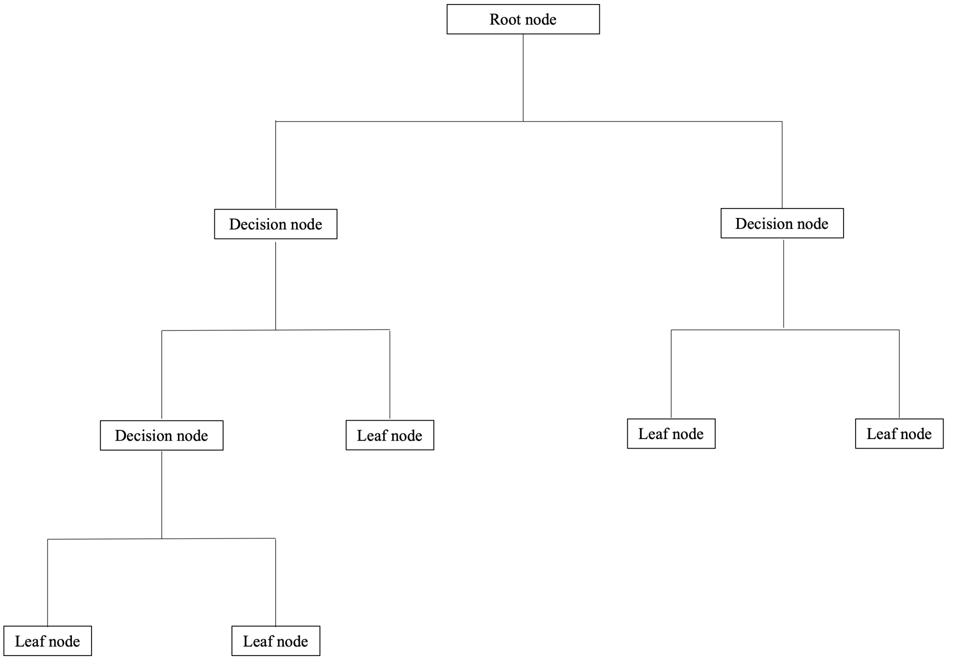

Figure A1. Example of a Decision Tree

The decision tree starts with the root node, which evaluates the whole data set in terms of one feature and separates the data into those that meet the root criterion and those that do not (Rokach & Maimon, 2005). For example, the root node can divide the data into observations with a value greater or equal to 6.0 within the valence dimension. Afterward, each decision node divides the data into subgroups by testing a single feature until finding a leaf node that only contains observations representing a pure class (e.g., EM group). Therefore, the decision tree algorithm continues to create decision nodes until it separates the data into groups containing only one unique class label (pure nodes). In some cases, the decision tree algorithm cannot decompose the data into pure nodes; however, it is always possible to set various hyperparameters, such as maximum depth. The "max_depth" determines the number of decision nodes performed in the tree (Probst et al., 2019). For instance, setting a maximum depth to 2 in Figure 1 would result in a tree with three leaf nodes and one decision node. Therefore, the "max_depth" parameter sets a limit to stop the node splitting.

First, the algorithm divides the dataset into a training and a test dataset to create a random forest (Breiman, 2001a; Fife & D'Onofrio, 2022). The training set is used to train the prediction model, and the test set is used to evaluate how well the model performs with unseen data once the prediction model is created. One of the most important characteristics of RF is that each individual tree within the forest is grown using a bootstrapped sample with replacement (Archer & Kimes, 2008), which refers to randomly selecting observations from the training set. This random selection is made with replacement, meaning that an observation can be selected multiple times for the same tree, so that each tree is trained with different observations (Probst et al., 2019).

In addition to bootstrapped samples, a second important aspect of RF is that each individual tree is formed by randomly selecting, at each node, a random feature to evaluate the decision node (Breiman, 2001a; Fife & D'Onofrio, 2022; Probst et al., 2019). For example, the RF generally samples $\sqrt{m}$ features to determine the root node, with m being the total number of variables that the dataset contains. After randomly sampling the features, the algorithm, among all possible splits, selects the feature that best splits the data. The random sampling of features continues at each individual node until a leaf node or "max_depth" is reached (Probst et al., 2019). One of the key benefits of random feature selection is that is helps to reduce the variance of the model. In addition, by randomly selecting a subset of features at each node, the model is less likely to be influenced by one individual feature. In general, bootstrapped sampling with replacement and random feature selection helps to create a more diverse set of decision trees. Consequently, the correlation between each individual decision tree within the forest decreases, reducing the chances of overfitting and improving the overall performance of the model.

Once all the decision trees are built, the trained model can be used to make predictions over the test data set. Based on input data (test dataset), the algorithm examines the predictions made by each tree and selects the class that the majority of trees have predicted (majority voting) (Speiser, 2021). For example, if a random forest contains 100 decision trees, 70 of which predict class EM and 30 predict class EL, then the random forest would predict class EM for that particular observation.

The RF algorithm has shown excellent results compared to other techniques, such as logistic regression, decision trees, neural nets, and k-nearest neighbors, among others (Breiman, 2001b). Another key advantage of RF is that it can detect interactions and non-linear effects without requiring the explicit modeling of these relationships (Fife & D'Onofrio, 2022). The RF can capture interactions by building multiple decision trees and averaging their predictions. Thus, exposing each feature to various combinations provides a comprehensive understanding of the complex relationship that a feature may have with the response.

RF is also capable of calculating feature importance using the Variable Importance (VI) metric. Variable importance measures the extent to which a feature contributes to the outcome or prediction of a model by calculating whether the prediction error increases or decreases when a specific feature is included in the model (Archer & Kimes, 2008; Fife & D'Onofrio, 2022; Strobl et al., 2009). It helps to select the most important features of the model in predicting an outcome. There are numerous ways to calculate the VI, such as the Gini index, z-score, permutation importance, or mean decrease in accuracy.

In addition, selecting a subset of the most relevant features might be helpful when working in high dimensional settings. The latter can be achieved by using Recursive Feature Elimination (RFE). RFE is a backward selection method that aims to reduce the number of features while preserving the predictive accuracy of the model (Wang et al., 2022). First, it removes the feature with the lowest relevance to the overall predictive performance. Subsequently, it recalculates the feature relevance and eliminates the second least relevant feature. This last process continues until only one feature remains.

This approach is efficient when working with correlated features since the impact of each feature on the predictive performance may change at each step of the backward elimination (Gregorutti et al., 2017). Therefore, rather than just calculating the relevance of each feature once, recalculating it at every step improves the feature selection process.

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4.3 Study 3: Does task difficulty increase semantic feedback? A study on the effects of valence during visual recognition of emotion- label and emotion-laden words

Abstract

Semantic richness is a multidimensional construct that includes different features (e.g., number of associates, number of senses, etc.). Words with greater semantic richness are recognized faster in the lexical decision task by creating a stronger semantic activation, which in turn results in a faster response via feedback to the lexical-level. The effects of semantic feedback are more evident in conditions where the discriminability of words and nonwords is more difficult. In this study, we examined whether valence is a feature of semantic richness by using three versions of a lexical decision task, which varied in difficulty. In Version 1, we used illegal nonwords; in Version 2, we used legal nonwords; in Version 3, we used pseudohomophones and legal nonwords with a high number of neighbors. We selected 336 Spanish words as our primary stimuli. They were divided into affective and neutral words. Among the affective words, there were words that make a direct reference to a specific emotion (emotion-label words, e.g., love) and words that do not make a direct reference to an emotion but that can provoke it (emotion-laden words, e.g., knife). Results showed an increase in reaction times across versions, confirming the increase in task difficulty. However, facilitative valence effects were only observed in Versions 2 and 3. Furthermore, no differences between EM and EL words were observed. The results are discussed in relation to other semantic richness features.

Introduction

Visual word recognition involves various types of information, including orthographic, lexical and semantic information. The amount of semantic information associated to a word is referred to as semantic richness. Hence, semantic richness is a multidimensional construct that refers to the quantity of semantic information associated with a word or idea (Pexman et al., 2008; Yap et al., 2015). In the context of psycholinguistics, semantic richness has been found to have an impact on word recognition. For instance, Pexman et al., (2007) reported that words with greater semantic richness were processed more quickly during word recognition tasks, even after accounting for other lexical and semantic variables (see also Duñabeitia et al., 2008; Pexman et al., 2008; Yap et al., 2011).

Different features contribute to semantic richness, including imageability (the extent to which a word evokes mental imagery; Evans et al., 2012), animacy (whether a word represents a living entity or an inanimate object; Bonin et al., 2019), number of associates (the number of related words or concepts that are associated with a target word; Balota et al., 2004), number of senses (the different meanings or interpretations that a word can have; Hoffman et al., 2013), and concreteness (the extent to which a word represents something abstract or concrete; (Goh et al., 2016), among others. All these features facilitate word recognition in lexical decision tasks (Goh et al., 2016; Yap et al., 2011, 2012). The lexical decision task (LDT) is the most common method used to evaluate visual word recognition. It is argued that the facilitative effects of semantic richness in the LDT are produced by semantic feedback from semantic representations to lower-level representations (semantic-level -> lexical level -> letter level; Brown et al., 2006). In this sense, visual word recognition should be understood as a highly interactive process that involves a bidirectional cascade flow of activation between lower-levels (bottom-up pathway) and higher levels (top-down pathway) of representation (Balota, 1990; Reimer et al., 2013; Yap et al., 2015). That is, information from one level can influence higher or lower levels of representation without the need for the process at any individual level to be completed. Therefore, when the reader encounters a semantically rich word, it elicits strong top-down feedback from the semantic level to the lower-level representations, facilitating lexical access.

The semantic feedback effect has been proposed to increase as the task difficulty increases due to an enhanced demand for higher-level processing (Pexman et al., 2008; Yap et al., 2012). This enhanced semantic feedback facilitates word recognition and decision-making (Bonin et al., 2019; Evans et al., 2012; O'Malley et al., 2007; Robidoux et al., 2010). Let us consider a lexical decision task in which a participant is presented with either a word or a nonword. In this scenario, the complexity of the lexical decision task can be increased or decreased by manipulating the resemblance of the nonwords to actual words. This approach has been used in a few studies. For example, Bonin et al., (2019) examined if animacy influences lexical decisions and if it can be considered as a basic semantic feature. These researchers compared animate concrete words (e.g., dog) and inanimate concrete words (e.g., house). They examined the animacy effect through two distinct lexical decision tasks in French: one involving legal nonwords (a string of letters that follows the phonotactic rules of a particular language but is not a real word) and the other incorporating a mix of difficult and easy nonwords. The easy nonwords were created using strings of letters that are illegal in the French language, making the task of identifying illegal nonwords very easy. The difficult nonwords had a greater resemblance to actual words and were either pseudohomphones (i.e., a nonword that is phonetically identical to a real word) or nonwords with a high number of neighbors (i.e., words that can be created by changing just one letter while maintaining the identity and position of the remaining letters). The results of the first experiment (legal nonwords) indicated that the mean lexical decision time for animate words was significantly faster than for inanimate words. In the second lexical decision task, a significant effect emerged in the difficult nonwords condition (pseudohomophones), where animate words displayed faster reaction times than inanimate words. However, no animacy effect was observed in the easy condition (illegal nonwords). Moreover, no differences in animacy effects were found in the comparison between the nonwords of moderate difficulty (legal nonwords) and the difficult nonwords (pseudohomophones). The authors concluded that animacy yielded a supplementary source of information leading to faster reaction times for animate words compared to inanimate words. In addition, the comparison between the illegal condition and the pseudohomophones condition, suggest that the animacy effect become salient when the nonwords exhibited greater word-likeness (word-likeness refers to the degree to which a nonword resemble the structure, phonetics, or appearance of a real word). Using a similar approach, Evans et al. (2012) examined to what extent imageability facilitates visual word recognition in English. These researchers manipulated the imageability of the words during a lexical decision task and a semantic priming task. They also manipulated the level of difficulty of the task by using different types of nonwords: consonant strings (e.g., "*bpk*"), legal nonwords (e.g., "*fet*"), and pseudohomphones (e.g., "*zew*"). Their results showed that high imageability led to faster reaction times on the legal and pseudohomophones tasks, but not on the illegal task. Moreover, the imageability effect became more pronounced as the nonwords became harder to discriminate from words. Their findings indicate that semantic effects are larger when the nonwords presented are more word-like, suggesting that increasing the difficulty of the task enables the semantic level to feedback to the lexical and letter levels, probably because of the greater amount of time required to perform the task.

Based on previous research, the present study aims to examine whether the affective information that a word conveys contributes to its semantic richness. The field of psycholinguistics has mainly used a dimensional approach to explore how affective content influences word processing. The dimensional models of emotions posit that the affective experience is fundamentally characterized along two primary dimensions: valence and arousal (Russell, 2003; Russell & Barrett, 1999). Valence is the extent to which a stimulus is negative or positive, which is often assessed on an unpleasant to pleasant scale (e.g., “hate” is an unpleasant or negative word, while “love” is a pleasant or positive word). On the other hand, the arousal dimension goes from low arousing to high arousing, which is the extent to which a stimulus is calming or exciting (e.g., “peace" is a low arousing word, while “party" is a high arousing word).

Research on the effects of affective content on word processing has compared affectively valenced words and non-affective (neutral) words, focusing on the role of valence. The results of these studies show that positive valence tends to facilitate word recognition (Hofmann et al., 2009; Kousta et al., 2009), while the effects of negative valence are less consistent: Some studies show advantages for negative words, while others report disadvantages or no significant effects. As an example, Kousta et al., (2009) observed a benefit of negative words over neutral words, whereas Estes and Adelman (2008) noted that negative stimuli led to slower response times than neutral ones. Moreover, some studies have found a significant arousal effect on word recognition (Kever et al., 2019), while others have reported and interaction between valence and arousal (see Hinojosa et al., 2020 for a review). Despite the reported differences between affective and neutral word processing, no study has assessed whether the valence effects are similar to those observed for variables such as imageability and animacy, which have been explained in terms of semantic richness (semantic feedback). Affective words may be semantically richer compared to neutral words because they contain affective information, that is not present in neutral words. In fact, emotional content has also been proposed as a feature of semantic richness (Yap et al., 2015). Here, we investigate whether valence behaves like other features associated to semantic richness (e.g., animacy, imageability), showing effects which are compatible with a semantic feedback mechanism.

Another relevant characteristic of affective words is that, in addition to displaying distinct valence and arousal values, they also exhibit variability in their association with emotional content. The affective word literature has urged researchers to consider the distinction between emotion label and emotion laden words (see Wu & Zhang, 2020 for a review). Both, emotion label words (EM words henceforth) and emotion laden words (EL words henceforth) are related to emotions. EM words directly label an emotion such as “happy” or “sad”, while EL words can elicit an emotion without explicitly labeling it (e.g., "knife", "mother"; Pavlenko, 2008). In this sense, there is an important difference in how these words become affectively loaded, since EM words refer to an emotion, whereas EL words can be associated with an emotion based on individual experience and the context in which they are used.

Therefore, it is important to compare EM and EL words. In fact, previous studies have reported some differences in processing between EM and EL in several paradigms and tasks, like an affective priming task (Wu et al., 2021; Kazanas & Altarriba 2016a), or the affective Simon task (Altarriba & Basnight-Brown, 2011). Differences have also been reported in the type of associated words produced by these two types of words (Betancourt et al., 2023), and in the patterns of brain activation elicited (Wang et al., 2019; Zhang et al., 2017; Zhang et al., 2020). Differences between EM and EL words also extend to the LDT, where faster reaction times have been reported for EM words compared to EL words (Kazanas & Altarriba, 2015, 2016b). However, although some studies using LDT have reported differences between EM and EL words, none has investigated yet whether these differences may be related to semantic feedback effects. On the other hand, recent studies (Betancourt et al., 2024) suggest that several affective properties, related with multi-componential models of emotion, are more relevant for the representation and organization in the lexicon of EM words than EL words. Specifically, the researchers created a semantic space and a prediction model to determine the unique affective characteristics that differentiate EM and EL words. To achieve this, they considered subjective ratings of different affective variables: action, assessment, expression, feeling, interoception, valence, and arousal (Scherer, 2001; Russell, 1980). The results show that, when considering all these variables, the EM words are characterized more precisely than EL words. These results suggest that EM words are associated with a greater amount of affective information and therefore could potentially be semantically richer.

In the present study we aimed to examine the effects of valence on affective (EM and EL words) processing and ascertain whether valence behaves as a feature of semantic richness. To test this, we focused on a LDT and created tree versions of varying difficulty. Task difficulty was manipulated through the type of nonword presented (version 1: illegal nonwords; version 2: legal nonwords; version 3: pseudohomphones and nonwords with a high number of lexical neighbors). According to Bonin et al. (2019) and Evans et al.(2012), as task difficulty increases, more information would be required to perform the lexical decision. Thus, we predicted that valence effects should become stronger as nonwords become more word-like. The second aim of this study was to explore if the impact of valence, expected to increase with task difficulty, exhibits a similar pattern in both EM and EL words or if the pattern differs between these two types of words. Assuming that EM words might be semantically richer in terms of affective content, we would expect the effects of valence to be stronger for EM words than for EL words.

Methods

Participants

A total of one hundred and twenty-nine participants took part in the experiment (females = 105, 81.4%; males = 24, 18.6%; whose mean age was 20.02, SD = 4.53). Participants were students at the Universitat Rovira i Virgili in Tarragona, Spain. Each participant completed only one version of the task in exchange of academic credit or as a volunteer. All participants signed an informed consent form before starting with the lexical decision task. The research was conducted in accordance with the APA ethical standards. Approval was granted by the Ethics Committee for Research on People, Society and the Environment of the Universitat Rovira i Virgili (CEIPSA-2021-PR-0044).

Materials

Words

A total of 336 Spanish nouns were selected as our primary stimuli for the lexical decision task. Each word belonged to one of three conditions: EM, EL, or neutral (NT words henceforth). The EM words were taken from the study of Pérez-Sánchez et al. (2021), while the EL and NT words were retrieved from Stadthagen-Gonzalez et al. (2017). We divided the stimuli into 84 EM words (42 positive and 42 negative), 84 EL words (42 positive and 42 negative), and 168 NT words. The EM, EL and NT words were matched on seven variables:

length, number of neighbors, OLD20, bigram frequency, number of syllables, log frequency (variables taken form EsPal, Duchon et al., 2013) and age of acquisition (taken from Alonso et al.,2015). In addition, we searched for the values of valence, arousal (Stadthagen-Gonzalez et al. 2017), and concreteness (Duchon et al., 2013, Guasch et al., 2016; Hinojosa et al., 2016, Huete et al., 2020 Pérez-Sánchez et al. 2021; all *p*'s > .18). Moreover, EM and EL words were matched in valence and arousal ($p > .05$), while EL and NT words were matched in concreteness ($p = .24$). Lastly, we collected ratings for animacy and imageability through a series of questionnaires. We constructed four questionnaires, each containing 168 words. The questionnaires were responded by a total of 66 participants (females = 35, 53%; males = 30, 45%; other = 1, 0.02%; whose mean age was 19.8, SD = 3.08).

Table 1. Characteristics of EM, EL, and NT words.

	EM	EL	NT
Age of Acquisition	8.27 (±1.9)	7.84 (±1.9)	7.84 (±1.9)
Animacy	3.70 (±0.4)	3.08 (±1.3)	2.68 (±1.6)
Arousal	6.06 (±1.4)	5.92 (±1.3)	5.18 (±0.8)
Valence	5.06 (±2.5)	5.03 (±2.4)	5.17 (±0.5)
Concreteness	3.97 (±0.4)	4.68 (±0.9)	4.85 (±1.1)
Imageability	4.18 (±0.7)	5.10 (±1.3)	5.4 (±1.3)
Log Frequency	0.82 (±0.7)	0.87 (±0.7)	0.77 (±0.5)
Length	7.93 (±2.2)	7.49 (±2.3)	7.69 (±2.3)
N (number of neighbors)	2.29 (3.5)	3.00 (±4.5)	3.25 (±5.4)
Number of syllables	3.31 (±0.9)	3.12 (±0.9)	3.18 (±1.0)
OLD20	2.29 (±0.7)	2.13 (±0.7)	2.15 (±0.7)
Bigram Frequency	24599.15 (±1098)	24297.83 (±1010)	25379.44 (±9385)

NOTE: All values are means and standard deviations (±).

Nonwords

A total of 336 nonwords were created for each version of the lexical decision task. The illegal nonwords (Version 1) were created by changing the vocals of the experimental words by consonants (e.g., *abrazo* = *qbrqzb, factura* = *fgctvrq, serenidad* = *scrnldqd*). The legal nonwords (Version 2) were created with the multilingual nonwords generator, Wuggy (Keuleers & Brysbaert, 2010; e.g., *prenevinio, grúdica*). Each legal nonword was created using an experimental word as a template (e.g., *carisma* = *calerma*). Lastly, the nonwords presented in Version 3 consisted of a mixture of pseudohomophones (words that sounded like actual words: *posibilidad* = *posivilidad, ingeniero* = *injenerio, rodilla* = *rodiya*) and nonwords with a high number of lexical neighbors (the average number of neighbors on version 3 was 4.73; min = 3, max = 13, while the average number of neighbors on version 2 was 0.32; min = 0, max = 5). The nonwords with a high number of neighbors were taken from Clearpond, a cross-linguistic database that provides phonological and orthographic neighborhood densities (Marian et al., 2012). The three types of nonwords were matched to the experimental words in length (all p's > .74). Finally, we verified that the nonwords were not real words in Spanish, English, and Catalan using the NIM search engine (Guasch et al., 2013).

Procedure

The procedure was the same for the three versions of the lexical decision task. Each trial began with the presentation of a fixation point ("+") displayed for 500ms. The fixation point ("+") was followed by a word/nonword appearing in the middle of the screen for 2,000ms or until participant's response. The task contained 336 words and 336 nonwords, presented in a randomized order.

Participants were instructed to decide whether the presented word/nonword was a Spanish word using a control keypad, with one key to answer "NO" (using the non-dominant hand) and another one to answer "YES" (using the dominant hand). The DMDX software (Forster & Forster, 2003) was used to present the stimuli and collect responses. Before the experiment, participants were presented with a practice block that consisted of 16 trials. The proportion of each type of stimulus in the practice trials was the same as in the experiment. Then the experiment started and there was a break in the middle of the experiment, and the duration of the experiment was around thirty-five minutes.

Data Analysis

We collected 86,688 observations from the 129 participants in the three versions of the lexical decision task. We removed participants with an error rate equal to or greater than 20%, which left us with 121 participants. In addition, we removed RTs under 300ms and the RTs that were two standard deviations above or below the mean, leaving a total of 76,771 observations for the analysis.

We analyzed the data using linear mixed-effect models (e.g., Baayen, 2008; Baayen et al., 2008). For this analysis, we used the *lme4* package from R (Bates et al., 2019). We created two independent linear models to examine 1) whether the type of pseudoword influences the valence effect, and 2) whether there are differences between EM and EL words in terms of the valence effect depending on each type of pseudoword. The analyses were performed on the inverse RTs (-1,000/RT).

In the first model, we analyzed the interaction between valence and task version. In order to perform this analysis, we introduced the inverse RTs as our dependent variable. As predictors we considered main effects of valence, task version, and other covariates, as well as the interaction between valence and task version. For the second model, we introduced the inverse RTs as our dependent variable and as predictors the main effects of valence, task version, type of word, and other covariates, as well as the interaction between valence, task version, and type of word (considering only EM and EL words). All the analyses also included several covariates for which there is evidence of their effect on LDT: age of acquisition, animacy, imageability, arousal, bigram frequency, concreteness, log frequency, length, number of neighbors, number of syllables, and OLD20 (see Table 1). Each covariate was normalized and centralized. Both models included random intercepts for participants and words, and none of them included random slopes due to convergence problems. We calculated multicollinearity among the fixed effects introduced in the different models and removed those with a VIF > 3 (Zuur et al., 2010). We removed length with a VIF value of 7.12 and imageability with a VIF of 3.14. To test if the interaction of interest significantly improves the fit of the model, we conducted a likelihood ratio test performing an ANOVA between a model with interaction and without interaction. The results of the likelihood ratio test are reported as a chi-square statistic (χ^2). We also report the results of the t-test analyses of the coefficient estimates for each fixed effect and interaction. To this end we used Satterthwaite's approximations to the degrees of freedom of the denominator (p-values were estimated by the *lmerTest* package, Kuznetsova et al., 2019). Subsequent post-hoc comparisons and effect sizes were conducted using the *emmeans* package.

Results

Model 1: Interaction of valence and task version

Table 2 displays the mean reaction times for each condition. The comparison of the first model showed that the task version interacted with valence (χ^2 (2) = 85.64, p < .001; see Table 3). Positive valence facilitated performance version 2 (legal nonwords) and version 3 (pseudohomophones and nonwords with high number of lexical neighbors), but not with version 1 which used illegal nonwords (version 1: estimate = 0.002, SD = 0.004, $t(317) = 0.40$, $p = .68$, effect size = -0.23; version 2: estimate = -0.017, SD = 0.008, $t(325) = 2.19$, $p = .03$, effect size = 0.26; version 3: estimate = -0.017, SD = 0.008, $t(332) = 2.24$, $p = .03$, effect size = 0.27, see Figure 1).

Table 2. Mean reaction times and standard deviations for each task.

Version	Mean RTs	SD RTs
Version 1	480	113
Version 2	642	189
Version 3	738	230

NOTE. Version 1 = illegal nonwords; Version 2 = legal nonwords; Version 3 = pseudohomophones and nonwords with a high number of lexical neighbors.

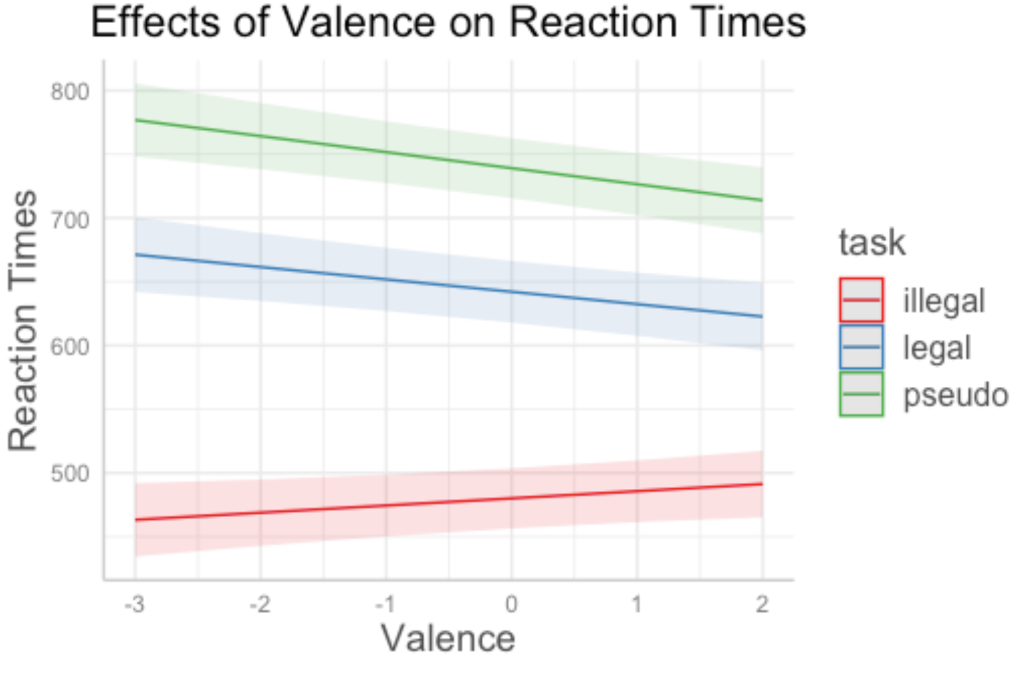
Table 3. Summary of the effects of the interaction between valence and task version.

	Estimate	SE	*t*	*p*
Intercept	-1.773	0.018	96.448	< .01
Valence	-0.010	0.005	2.051	.04
Version 1	0.258	0.022	11.74	< .01
Version 2	0.153	0.012	12.161	< .01
Arousal	-0.002	0.005	0.445	.65
Animacy	-0.001	0.004	0.302	.76
Age of Acquisition	0.018	0.005	3.125	< .01
Number of Neighbors	0.014	0.006	2.324	.02
Number of Syllables	0.007	0.006	1.098	.27
OLD20	0.031	0.007	4.196	< .01

Bigram Frequency	0.012	0.004	2.7	.01
Concreteness	0.019	0.005	3.792	< .01
Frequency	-0.064	0.005	11.279	< .01
Valence: Version 1	-0.017	0.002	7.965	< .01
Valence: Version 2	-0.005	0.001	4.688	< .01

NOTE. The reference level (task) used to analyze the intercept is the version 3.

Figure 1. Valence effect and Task version



NOTE. illegal = version 1; legal = version 2; pseudo = version 3.

Model 2: Interaction of valence, word type, and task version

The second objective of the study was to explore if valence exhibited similar effects in EM and EL words in the three versions of the lexical decision task. Table 4 displays the mean reaction times for each word type in each task version. There was no main effect of valence and word type. In addition, our findings indicate that there was no interaction between valence, word type, and task version (χ^2 (2) = 2.31 p < .32; see Table 5 and Figure 2).

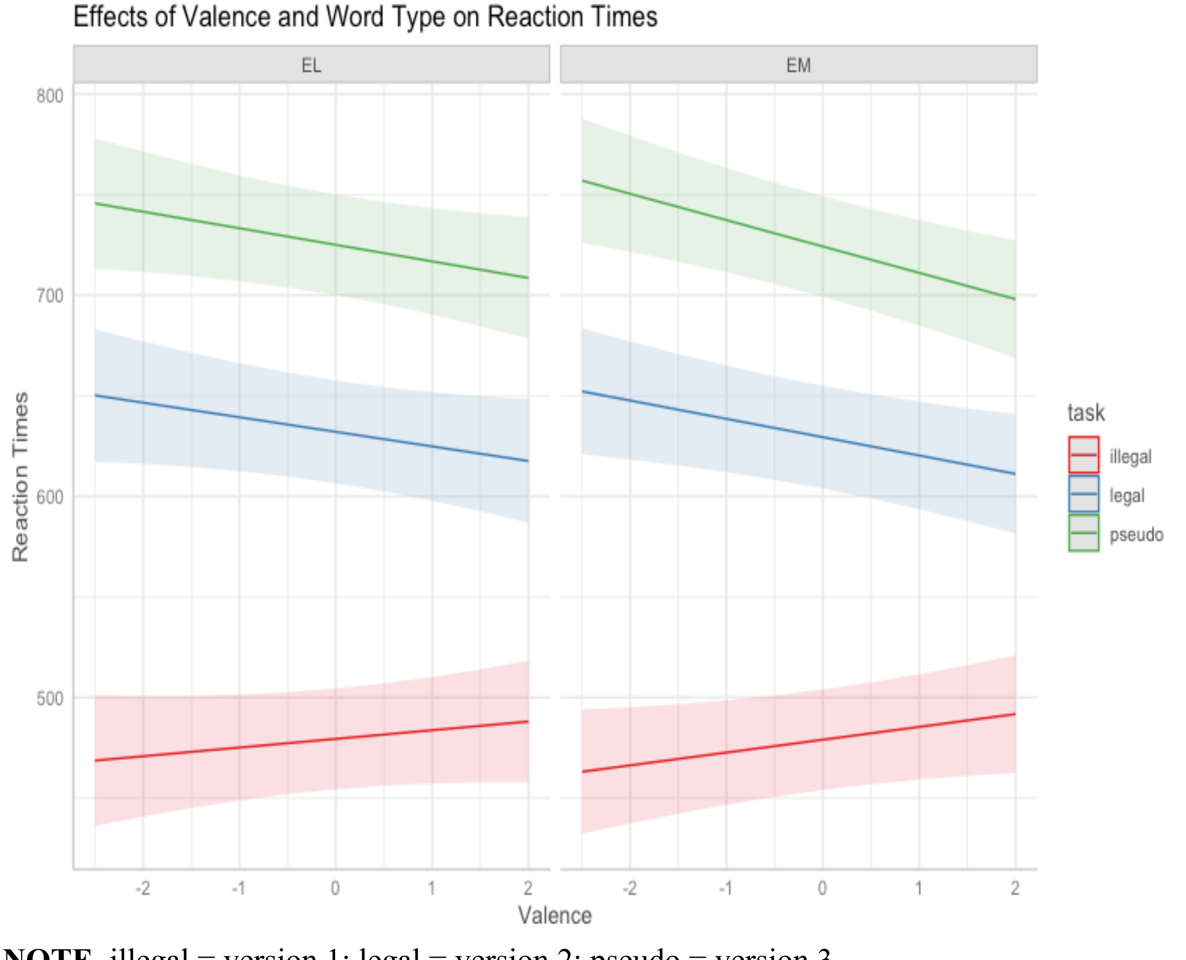
Table 4. Mean reaction times and standard deviations for word type in each task version.

Task Version 1: Illegal		
Word Type	Mean RTs	SD RTs
EM	479	113
EL	480	114
NT	481	113
Task Version 2: Legal		
Word Type	Mean RTs	SD RTs
EM	629	189
EL	633	183
NT	653	191

Task Version 3: Pseudohomophones and high number of lexical neighbors

Word Type	Mean RTs	SD RTs
EM	723	228
EL	724	225
NT	752	233

Figure 2. Valence effect in EM and EL words in the three versions of the task.



NOTE. illegal = version 1; legal = version 2; pseudo = version 3.

Table 5. Summary of the effects of the interaction between valence, type of word, and task version.

	Estimate	*SE*	*t*	*p*
Intercept	-1.777	0.020	88.057	< .01
Version 1	0.250	0.022	11.179	< .01
Version 2	0.149	0.013	11.623	<.01
Type EM	-0.011	0.015	0.701	.484
Valence	-0.008	0.008	0.954	.341
Arousal	-0.001	0.007	0.192	.848
Animacy	-0.013	0.009	1.393	.166
Age of Acquisition	0.011	0.009	1.243	.216
Number of Neighbors	0.024	0.011	2.170	.032
Number of Syllables	0.009	0.009	1.010	.314
OLD 20	0.034	0.011	3.142	.002
Bigram Frequency	0.011	0.006	1.717	.088
Concreteness	0.011	0.009	1.124	.263
Frequency	-0.064	0.008	8.031	< .01
Version 1: type EM	-0.008	0.006	1.255	.209
Version 2: type EM	-0.001	0.004	0.020	.984
Version 1: Valence	-0.014	0.003	4.380	< .01
Version 2: Valence	-0.003	0.002	1.694	.090
Type EM: Valence	-0.002	0.009	0.209	.835

Version 1: type EM: Valence	-0.002	0.004	0.468	.639
Version 2: type EM: Valence	-0.004	0.003	1.445	.149

NOTE. The reference level (task) used to analyze the intercept is the version 3.

Discussion

The aim of this study was to test whether valence behaves as a feature of semantic richness, and to examine if valence effects exhibit similar patterns on EM and EL words. To this end, we conducted a lexical decision task with three versions of varying difficulty based on the similarity of the presented nonwords to real words. We found that positive valence improved performance on version 2 (moderate difficulty) and version 3 (high difficulty), but it did not have an impact on version 1 (low difficulty). Furthermore, we found no significant differences in the effects of valence on EM and EL words during lexical decision with different levels of difficulty.

Based on previous findings (Bonin et al., 2019; Evans et al., 2012; Yap et al., 2015), we hypothesized that as the nonwords became more difficult, the participants would rely more on semantic feedback to solve the lexical decision, amplifying the valence effects. As expected, our results indicate that there was a notable increase in the mean reaction times across the three versions of the lexical decision task (version 1: 480ms; version 2: 642ms; version 3: 738ms;

see Table 2), suggesting that the discrimination between nonwords and words became increasingly more difficult. This increase in the mean reaction times is in line with the findings reported in Evans et al., (2012), where a consistent increase in mean reaction times was observed across different levels of task difficulty. Additionally, our results showed that valence influences reaction times during lexical decision. Specifically, we observed that positive valence facilitated word recognition on version 2 and version 3. Thus, our results indicate that positive valenced words are recognized faster than neutral and negative words. Previous studies have also observed this facilitation effect for words with a positive valence (Kazanas & Altarriba, 2015; Kuperman et al., 2014; Ponari et al., 2015).

Moreover, our results indicate that there was an interaction between valence and task version. The results showed that there were no significant effects on the illegal task. It is important to remember that illegal nonwords were constructed using a string of consonants. These strings did not form recognizable words in Spanish or other language (i.e., "*qbrqzb*"). Because of this unique construction, these nonwords might have been easily distinguished from actual words. As a result, participants might have found this consonant-only nonword “too easy" to identify as a nonword, leading to quicker reaction times. In other words, the speed of the task completion may have prevented semantic information to become influential, causing a more surface-level, or orthographic, processing. In this case, participants could discriminate words based on their form, familiarity, or other strategies.

More importantly, significant effects were observed for version 2 and version 3, suggesting that valence effects only become more pronounced when task difficulty increases. Furthermore, although we found a valence effect when we compared the illegal task to the legal and pseudohomophones task, no differences were observed on the comparison between the legal and pseudohomophones task, which suggest that the valence effect remained constant through the more difficult tasks. Our results are in line with those reported in Bonin et al. (2019), in which they observed animacy effects when comparing the illegal task to the pseudohomophones task, but no differences were observed when comparing the legal and the pseudohomophones tasks. The findings reported here and in Bonin et al., (2019), are consistent to some extent with those reported in Evans et al., (2012). In the study of Evans et al., (2012), the researchers observed a constant increase in the imageability effect as the nonword became more wordlike. In other words, they found that as the decisions became harder, the advantage of high imageability became stronger, leading to differences between an illegal task compared to a legal task and between a legal task compared to a pseudohomophones task. Explanations of semantic richness effects suggest that semantic features generate stronger semantic activation under conditions where it is more difficult to discriminate between a nonword and a word (O'Malley et al., 2007; Pexman et al., 2002;

Pexman et al., 2008; Yap et al., 2012). Our results showed that the valence effects did not increase from moderate difficulty version (version 2) to high difficulty version (version 3), suggesting that valence does not completely behave as a feature of semantic richness. Forthcoming research should explore further this issue and examine valence effects across different cognitive tasks/demands. In addition, future studies should explore this issue with more sensitive measures, including event-related potentials (ERPs) to analyze components sensitive to the level of semantic processing. These studies can shed light on the activation, integration, and influence of semantic information during word recognition, contributing to a better understanding of how these semantic features behave.

On the other hand, our second objective was to explore if the valence effects behave differently in EM and EL words. For this purpose, we examined whether there was a three-way interaction between valence, type of nonword, and task version. There was no main effect of type of word. At the same time, the interaction between valence, type of word (EM and EL words), and task version was not significant. In other words, the valence effects on EM and EL words remain constant through the different task versions. Some studies have reported differences between EM and EL words (Zhang et al., 2019), while others have not observed such distinctions (Martin & Altarriba, 2017). Our results are similar to those presented in Martin and Altarriba (2017), in which no differences were identified. The discrepancy in the findings across different studies demonstrates a lack of consistency in the literature. Such inconsistency emphasizes the need for further investigation into the distinction between EM and EL words. Further, previous research has shown that EM words are associated with a greater amount of affective information (Betancourt et al., 2024), leading to the assumption that they might be semantically richer. However, the results presented here show no differences between EM and EL words.

In general, the lexical decision task helps us to evaluate the semantic feedback effect. The semantic feedback is expected to increase as task difficulty increases. Consistent with the semantic feedback proposal, we observed a valence effect for tasks of moderate to high difficulty, but not for tasks of low difficulty, which are associated with more surface-level processing, and therefore do not require semantic feedback to solve the task. However, based on the semantic feedback effect we would expect a consistent increase of the valence effect as the task difficulty increases. Instead, we were not able to find differences between the moderate difficulty version and the high difficulty version. In this sense, our results do not conclusively demonstrate that valence is a feature of semantic richness. Nonetheless, the conclusions drawn from our research do not undermine the significance of valence during the process of word recognition. Lastly, our results cannot confirm any further differences between EM and EL words regarding valence. Future studies interested in the distinction between EM and EL words should dig deeper into the underlying components of emotions that shape the affective responses on EM and EL words.

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PART III

FINAL REMARKS

CHAPTER V: General Discussion and Conclusions

5.1 Discussion

In past decades, the relationship between language, cognition and emotion has become a major area of interest in psycholinguistics (Citron, 2012; Citron et al. 2014; Hinojosa et al. 2020a, b; Wu & Zhang, 2020). Within this field, a particular focus has been on understanding how we process emotional or affective words (Altarriba & Canary, 2004; Chen et al. 2015; Delaney-Busch et al. 2016; Haro et al. 2022; Kazanas & Altarriba, 2016; Knickerbocker et al. 2019; Wang et al. 2019; Zhang et al. 2020). The vast majority of studies exploring the relationship between language and emotion have adopted a dimensional approach, characterizing affective features along two basic dimensions: valence and arousal (Russell, 1980, 2003). Several researchers have found that affective features (valence and arousal) have an impact in how we process words in our minds (see Hinojosa et al. 2020 for a review). In addition, previous research also highlights an important distinction between affective words: EM words (emotion-label words), which directly label emotions, such as "love" or "hate," and EL words (emotion-laden words), which are words that do not directly label an emotion but can evoke it, such as "knife" or "party" (Pavlenko, 2008; see Wu et al. 2020 for a review).

In the present work, we had two primary objectives. The first one was to investigate the mental representation and organization of emotional EM and EL words in the lexicon. The second objective concerns affective word processing and was twofold: to examine whether valence can be considered a feature of semantic richness, and whether EM and EL words are processed differently in terms of valence effects. We addressed these objectives by conducting three separate studies. Studies 1 and 2 addressed the first primary objective, while Study 3 addressed the second primary objective. In the following, we discuss the results of these studies in relation to the two primary objectives of the thesis.

In Study 1, based on free association norms, we examined the contribution of affective content to the organization of words in the lexicon. The study has two parts. In the first part, we analyzed the associative structure of 840 Spanish EM, EL, NT cue words. The results of this analysis demonstrate that the most frequently produced associate for each category matched the category of the cue word, suggesting that word type may be an organizing principle in semantic memory. For instance, an EM cue word most frequently elicited an EM word as an associate. In addition, we found that EM associates produced in response to EM cues were more prototypical than EM associates produced in response to EL cues. In other words, when participants were cued with a word that directly labeled an emotion (EM), the EM words they produced in response were more representative of an emotion concept (i.e., they had a higher emotional prototypicality) than the EM words produced in response to an EL cue. For instance, the EM cue word *"desesperanza"* (hopelessness) elicited the associated EM word *"tristeza"* (sadness), which had a high prototypicality value of 4.91. Conversely, the EL cue word *"juego"* (game) elicited the associated EM word *"diversión*" (fun), with a lower prototypicality value of 3.05. Some studies have demonstrated that emotional prototypicality is a reliable index of the extent to which a particular word is a good representative of the category "emotion". For example, some researchers have reported that words with high prototypicality show shorter response times in an emotion categorization task, a task in which participants must decide as quickly as possible whether the presented word refers to an emotion or not (Niedenthal et al. 2004). On the other hand, emotional prototypicality affects the processing of EM words. For instance, Haro et al. (2022) aimed to study the role of emotional prototypicality during word recognition using an LDT. To that end, the authors conducted two LDT in which they examined if emotional prototypicality facilitates word recognition when controlling for other affective (e.g., valence, arousal), and lexico-semantic (e.g., frequency, concreteness) variables. Their results demonstrate that emotional prototypicality facilitates the processing and recognition of EM words.

Moreover, the results of this study demonstrate that words that explicitly label an emotion (EM words) are produced as associates to a greater extent for EL cues than for NT cues. This suggests that EM words are essential for the associative structure of EL words, suggesting that EL words may be related to an emotional process through their association with EM words. Thus, our results highlight a close relationship between EL and EM words at a representational level. However, the EM words did not produce more EL associates than the NT words. In other words, when an EL word like "*secuestro*" (abduction) is presented, it activates an EM word like "*miedo*" (fear). Conversely, the presentation of an EM word such as "*miedo*" (fear) does not directly activate and emotion eliciting word (EL) such as "*secuestro*" (abduction), but instead tends to lead to another EM word such as "*temor*" (dread). This also suggests that EM words are more closely related in our minds. This is consistent with research showing that EM words have a stronger priming effect compared to EL words (Kazanas & Altarriba, 2015, 2016). Such observations suggest a tighter organization of EM words in the lexicon compared to EL words. Furthermore, NT cues elicited a higher number of EL associates compared to EM cues. This result may be related to the similarity between the two types of words (EL and NT) regarding their degree of concreteness. These findings are consistent with those reported by Buades-Sitjar et al. (2021) who concluded that word association is clearly influenced by concreteness, valence, and arousal. We further confirmed these findings in the second part of the first study. In general, the results of this first part indicate that EM and EL words do not lead to similar word associations. It seems that the emotional nature of EM words is more salient and, as a result, connections to other EM words or affective states are prioritized. These emotional connections seem to be less salient in EL words, which possess a more indirect link to affective states.

In the second part of the study, we examined whether the affective (valence and arousal) and lexico-semantic features (concreteness, frequency, and age of acquisition) showed assortativity, which refers to the correspondence between the features of the cue words (i.e., valence, concreteness) and their associates. We first analyzed the three types of cue words together, finding that valence, arousal, concreteness, and age of acquisition exhibited assortativity. Specifically, valence showed the highest predictive capacity of all variables, followed by arousal. In addition, concreteness and, to a lesser extent, age of acquisition showed good predictive capacity. Second, we examined assortativity for EM, EL, and NT cues separately. The results revealed that valence and arousal were the only variables that showed assortativity for EM cues and their associates. In contrast, valence, arousal, and concreteness showed assortativity for EL cue words. Finally, concreteness, age of acquisition, and valence showed assortativity in the analysis of NT cue words and their associates. Our results show that valence is the only variable that exhibited assortativity across all three word types. In general, this finding provides an important insight into the associative patterns of affective and non-affective words, indicating that affective content plays an important role in the organization of the associative structure of both types of words. Specifically, these results highlight the importance of valence in connecting two words within an associative network.

Similar to Study 1, in Study 2 we focused on the representation and organization of affective words in the lexicon. The first objective of this study was to examine the contribution of affective features to the organization of words in the mental lexicon by creating a multidimensional semantic space using a Principal Component Analysis (PCA). To this end, we included affective features from two models: the Two-Dimensional Model and the Component Process Model (CPM). Thus, we considered valence, arousal, interoception, expression, appraisal, action, and feeling. The results of our PCA revealed a two-dimensional solution that explained 84.73% of the total variance. The first principal component (PC1) accounted for 59.69% of this variance and included the variables of interoception, expression, evaluation, action, and feeling. The second principal component (PC2) explained an additional 25.04% of the total variance and was composed of valence and arousal, where valence is the feature that contributes the most to the explained variability. The results of the PC2 indicate that valence and arousal are necessary to discriminate between affective (EM and EL) and neutral words. In fact, the results showed that NT words are characterized by mid-levels of valence scores and low levels of activation, while EM and EL words are characterized by extreme levels of valence, and varying levels of activation. Therefore, EM and EL words are similarly plotted in terms of the PC2. In this sense, characterizing EM and EL words based on valence and arousal alone is insufficient, because this helps us to discriminate between affective and NT words, but not between EM and EL words. In addition, the results of the PCA indicate that EM words are more closely related to the PC1 variables (derived from CPM) compared to EL and NT words. Therefore, what seems to differentiate EM and EL words is their close association with the CPM variables. These results are consistent with those reported in Scherer and Fontaine (2018), who studied the semantic structure of EM words in different languages and, using a regression analysis, found that the CPM is consistent with the semantic structure of these words.

The second objective of Study 2 was to investigate which features contribute most to the prediction of each word category, using the same variables as those included in the PCA. To this end, we performed a Random Forest Classifier (RFC) and examined the Mean Decrease in Accuracy (MDA). The results showed that valence, expression, action and assessment are good predictors of EL words, with valence as the most important predictor, improving the model's ability to predict EL words by 28.95%. On the other hand, our results showed that the CPM variables are more influential in determining whether words are classified as EM words. Indeed, each of the affective features included in the study contributed positively to the prediction of EM words, with feeling as the most significant predictor. For instance, the inclusion of feeling improved the model's capacity to predict EM words by

23.59%. Notably, following feeling, interoception, assessment, and expression were the next most important predictors of EM words, each enhancing the prediction accuracy by 16.69%. Finally, valence was the only variable that positively improved the prediction of NT words, improving the model's the predictive ability in the classification of the NT words by 12.87%.

The results of Study 2 are consistent with those obtained by Ferré et al. (2023). These authors examined the main features that predict emotional prototypicality (the extent to which a word exemplifies a particular emotion) in EM words. Their results showed that the CPM variables of feeling and interoception were the most significant predictors. The result of our study confirms this pattern. In our study, the feeling component emerged as the most influential feature in predicting EM words, closely followed by the interoception component. In contrast, this pattern was not observed for EL words for which the CPM variables exhibited a reduced predictive capacity. Therefore, we demonstrate for the first time that CPM variables are particularly effective in distinguishing between EM and EL words. This differentiation is likely due to the feeling component's capacity to facilitate the identification and categorization of specific emotions.

As evidenced in both Studies 1 and 2, valence consistently stands out as the most relevant factor for defining the affective space of all word types. For instance, in Study 1, valence is the only variable that shows assortativity for EM, EL, and NT words. In other words, these results indicate that the valence of the cue word is a strong predictor of the valence of the associated word, regardless of word type. Similarly, in Study 1, the MDA analysis revealed that valence is the only variable that positively affects the prediction of EM, EL, and NT words. In agreement with the two dimensional account (Russell, 1980, 2003; Russell & Barrett, 1999), these studies demonstrate that valence is one of the most fundamental components of affective content. The importance of valence is emphasized not only in the two-dimensional models, but also in the CPM. In fact, valence is thought to play an important role in the early stages of appraisal, wherein the organism evaluates the degree of pleasantness or unpleasantness in response to an event or stimulus. Valence describes the positive or negative character of emotions that largely derives from a psychological process of valuation (Barrett, 2006; Russell, 2003; Russell & Barrett, 1999). This positive and negative valuation seems to play an important role in the associative network of words and in how we self-report the emotion elicited of denoted by a certain word.

It is important to note that, according to our results, arousal does not seem to be a variable as fundamental as valence in the characterization of the affective properties of words and in their organization in the lexicon. In agreement with this, there is more agreement in subjective ratings of valence than arousal in normative studies (e.g., Pérez-Sánchez et al. 2021). Valence seems to be a fundamental aspect of affective content, it is activated very early when we are confronted with a stimulus or situation and is easy to understand for raters. On the other hand, arousal is a broader concept, making it more difficult to comprehend, that encompasses different sources of the emotional domain, such as action tendencies, motor expression, and bodily reactions. The CPM understands these physiological experiences as distinct components that are activated after the appraisal process has been initiated. In contrast, valence is described as more primitive and universal, occurring at a very early stage of the emotion process (Scherer et al. 2001). In this sense, valence plays an important role in initiating and shaping the emotion experience. This may explain why valence, as opposed to arousal, emerges as the most important variable in describing the affective space of words.

Although valence plays an important role in characterizing the affective content of words, it is not sufficient on its own to distinguish between EM and EL words. In fact, several studies demonstrate that, despite being matched in terms of valence, EM and EL words behave differently in several experimental paradigms (Kazanas and Altarriba, 2015; Kazanas and Altarriba, 2016; Wu et al. 2021; Zhang et al., 2019). More importantly, while our studies show that valence is the basic component of affective experience, they also show that CPM variables need to be incorporated to correctly distinguish between EM words and EL words. These results suggest that EM words are part of a more complex and dynamic emotion process that mainly involves different components, leading to the categorization (or labeling) of an emotion episode (feeling). Specifically, our results show that feeling and interoception are the most relevant variables in describing EM words. Therefore, words related to physiological changes and feelings are likely to be the best representatives of emotions. In other words, our results suggest that EM words can be clearly distinguished from EL words by different profiles of physiological responses. More importantly, they can be clearly distinguished in terms of the integrated information from different components that ultimately lead the individual to categorize or label an emotion.

In general, Studies 1 and 2 indicate that EM and EL words are strongly characterized by their association with a positive or negative emotion. However, the only way to distinguish between them is to focus on more than two components. Therefore, even though valence (how positive or negative is a word) is an important factor in describing the emotional experience, as proposed by both dimensional and CPM theories, the arousal dimension is a broad construct that does not help us differentiate the intensity of the feeling, bodily activation, and action tendencies associated to EM and EL words. For this reason, the CPM, in comparison with the dimensional account, seems to be a more appropriate approach to correctly distinguish between the two types of affective words.

In what follows, we discuss the results of Study 3, related with the second primary objective of the present thesis. The specific aims of this study were 1) to determine whether valence can be considered a feature of semantic richness, and, if this is the case, 2) to examine whether the effects of valence behave similarly or differently in EM and EL words. Affective content is part of the denotative meaning of EM words but not EL words. Furthermore, the results of Study 2 demonstrated that EM words have more information about several emotion variables (e.g., interoception and feeling) than EL words. Therefore, we speculated that EM words may be semantically richer than EL words, and thus, valence effects might be greater for EM words than for EL words. To test this, we created three versions of the same lexical decision task, each with a different difficulty level. In version one, we used illegal nonwords (low difficulty), the second version was created using legal nonwords (moderate difficulty), and the third version was created using pseudohomophones and legal nonwords with many lexical neighbors (high difficulty).

Regarding the first aim, the results showed an interaction between valence and task version. In version one (low difficulty) we did not observe a significant effect of valence. However, a significant effect of valence was observed on versions two and three, in which positive valence facilitated performance. Nonetheless, no differences on valence effects were observed between version two and three. In both of these versions our results indicate that positive valenced words are processed faster than neutral and negative valenced words. However, these effects did not increase between these versions, meaning that valence effects only increase between low to moderate or low to high difficulty, but not between moderate to high difficulty. The proposal of semantic richness effects suggest that semantic features generate stronger semantic activation under conditions where it is more difficult to discriminate between a word and a nonword (O'Malley et al. 2007; Pexman et al., 2002; Pexman et al. 2008; Yap et al. 2012). Our results showed that the valence effects did not increase from moderate difficulty version (version 2) to high difficulty version (version 3), suggesting that valence does not completely behave as a feature of semantic richness.

The results reported here are in line with those obtained by Bonin et al., (2019), in which, studying the animacy effect, the researchers found differences in the magnitude of the effect between the easy and the two other more difficult versions of the LDT, while no differences were observed between the moderate and high difficulty condition. In contrast, Evans et al. (2012) observed a consistent increase in reaction times as task difficulty increased. More importantly, they observed that the size of the imageability effect (i.e., the advantage in word recognition for high imageability words compared to low imageability words) increased gradually with the difficulty of nonwords, in line with the predictions about semantic richness. Therefore, we cannot completely discard that valence is a feature that contributes to semantic richness, because it behaves similar to other variables (i.e., animacy) but not others (i.e., imageability). It may be that the paradigm used here (i.e., the manipulation of nonword difficulty) does not capture the effects of all the variables associated to semantic richness.

Regarding the second aim of the study, we examined if valence effects behave differently in EM and EL words. There was no main effect of type of word. Therefore, our results cannot confirm any differences between the processing of EM and EL words. Importantly, the results in this field are mixed. For instance, Altarriba and Basnight-Brown (2011), Kazanas and Altarriba (2015), and Knickerbocker and Altarriba (2013) reported differences in word processing between these two word types. Conversely, Martin and Altarriba (2017) and Vinson et al. (2014), failed to find significant differences between EM and EL words. Differences in the experimental paradigms used or the lack of control of some relevant variables (e.g., EM words tend to be more abstract than EL words) may have contributed to the mixed findings. Finally, and more related to the aim of this study, the three-way interaction between valence, type of word (EM vs. EL) and task version was not significant. However, considering that valence did not show exactly the expected effect (i.e., a gradual effect in relation to increased task difficulty), we cannot reach a clear conclusion regarding the possible impact of the EM-EL differentiation on the modulation of valence effects by task difficulty.

Richer semantic representations typically allow for faster and more accurate word recognition (Yap et al. 2015). Valence has been proposed to be a feature of semantic richness (Pexman et al. 2008). Furthermore, affective words (EM and EL) are thought to be organized in terms of how positive or negative they are. In fact, the findings of Study 1 and 2 this thesis demonstrate that valence is the basic building block of affective word content, playing a key role in how we represent and organize words in our minds. However, results of Study 3 are not conclusive, regarding the consideration of valence as a feature of semantic richness. Moreover, the distinction between EM and EL words do not seem to have a role there.

In general, in the present thesis we aimed to understand how we represent and process EM and EL words. We studied this from different approaches, by relying on lexical association, multi-dimensional methods, prediction models and the analysis of valence effects on word recognition tasks. Based on our results, we argue that the concept of valence is the primary characteristic of every emotion that goes from highly pleasant (positive) to highly unpleasant (negative). Indeed, valence is one of the primary variables to predict the characteristics of associated words, and in determining the organization of words in the lexicon. Thus, valence is at the core of the affective experience of both EM and EL words. However, distinguishing these two types of words is only possible if we incorporate CPM variables.

5.2 Limitations and future studies

One possible limitation of the first two studies is the number of observations considered. While the Study 1 included 840 words and the Study 2 included 800 words, a larger number of stimuli could offer a more comprehensive representation of the associative structure and semantic space of affective words. Specifically, in Study 1, more observations could lead us to explore the lexico-semantic system as a network, revealing more complex relationships between each word type. Our results suggest that EM words are more central hubs, forming numerous connections with words that are associated with emotions. This could potentially explain the strong links from EL to EM words and the weak connection from EM to EL words. In other words, since EM words seem to have more connections with other affective words, their links or associative strength might be weaker. Conversely, EL having fewer connections to affective words, might exhibit a stronger link or associative strength with other affective words. These intuitions may be confirmed in a study involving far more words than those used here.

Moreover, in the second study, we created a prediction model using a random forest technique. In this study, we worked with an unbalanced dataset, with fewer EM words than EL and NT words. This is because the world of EM words is much smaller than that of the other groups. These models work well with unbalanced datasets. More interestingly, there are techniques that enable us to effectively handle datasets with even more significant imbalances

(Krawczyk. 2016; Fernández et al., 2018). Future studies could utilize these techniques to include a broader range (e.g., including an entire database) of EM, EL, and NT words, thereby enhancing the model's predictive power and our understanding of the impact of various variables on different word types. These models could also integrate linguistic data (word ratings) from diverse groups, including different personality traits, age groups (children, adults, older adults), or clinical vs. non-clinical groups, to comprehend the importance of different variables in different populations. In addition, it could be possible to develop a predictive model using data from various groups, enabling the model to classify them based on distinct linguistic variables. In other words, this would use linguistic data as a kind of marker to distinguish between different populations/disorders. This could potentially have practical applications in the field.

On the other hand, in the third and final study we conducted an LDT. To test whether valence behaves as a feature of semantic richness, we created different versions of the same LDT with varying levels of difficulty. However, the results were not clear and it may be that the paradigm is not completely sensitive to semantic richness effects. A possibility is to look for other manipulations to increase task difficulty. This could be achieved by visually degrading the stimulus quality of the legal nonwords or the pseudhomophones. In fact, previous studies have demonstrated that semantic feedback effects increase when the quality of the stimulus is manipulated (Reimer et al. 2013).

Furthermore, the third study could benefit from using a more sensitive measure, such as ERP, examining whether the components typically associated to emotional content (i.e., EPN and LPC) are modulated by task difficulty.

Additionally, future studies could aim to validate the semantic space created here by conducting a semantic priming study, in which word pairs are selected depending on the distances in the semantic space. The speed and ease with which participants respond to the target should be directly related to the distance between prime and target word. That is, we would expect greater prime-target facilitation when they are close together in semantic space, compared to prime-target pairs that are farther apart.

5.3 Conclusions

To sum up, the conclusions that can be drawn from the present thesis are the following:

To sum up, the conclusions that can be drawn from the present thesis are the following:

1. The affective category of the most frequently produced associate in a free association task is congruent with the affective category of the cue word.
2. EM words are closely related to other EM words with high emotional prototypicality ratings.
3. EM words are strongly connected to EM words, and weakly connected to EL words.
4. EL words are strongly connected to both EM and EL words.
5. Valence is the only variable that displays assortativity in EM, EL, and NT words. In other words, valence is strongly related to how words are connected in an associative structure.
6. The differences between affective (EM and EL) and neutral words predominantly arises from differences in valence.
7. On a representational level, the distinction between EM and EL words is only achieved if we include CPM-related variables.

8. The CPM provides a more comprehensive approach to accurately differentiating between EM and EL words than the dimensional account.
9. Valence is the central dimension of the affective content of words.
10. Valence cannot be fully considered as a feature of semantic richness.

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