Preregistration: The interplay between linguistic and embodied systems in conceptual processing

Pablo Bernabeu, Dermot Lynott and Louise Connell

Department of Psychology, Lancaster University

Author note

Pablo Bernabeu https://orcid.org/0000-0003-1083-2460

Dermot Lynott https://orcid.org/0000-0001-7338-0567

Louise Connell https://orcid.org/0000-0002-5291-5267

This preregistration is formed of nine literature-driven, confirmatory research questions. The analyses have not been conducted. Due to the broad scope of the research questions, the findings could be disseminated in more than a one paper. Upon completion, all data and analyses will be made available at https://osf.io/np6hy/.

Correspondence: Pablo Bernabeu (p.bernabeu@lancaster.ac.uk)

Abstract

This preregistration outlines a study that will investigate the dynamic nature of conceptual processing by examining the interplay between linguistic distributional systems—comprising word co-occurrence and word association—and embodied systems—comprising sensorimotor and emotional information. A set of confirmatory research questions are addressed using data from the Calgary Semantic Decision project, along with additional measures for the stimuli corresponding to distributional language statistics, embodied information, and individual differences in vocabulary size.

Keywords: conceptual processing, word recognition, semantic decision, linguistic distributional knowledge, embodied cognition

Contents

Conceptual processing—that is, the comprehension of content words (nouns, adjectives, verbs, adverbs)—is a dynamic, multidimensional process drawing on various kinds of information, as shown by word recognition experiments. Firstly, a major role is played by linguistic information, which refers to a person's active or latent knowledge about common associations among words. Secondly, there is the contribution of embodied information, which encompasses the perceptual, motor, emotional and social experience associated with concepts (Andrews et al., 2009; Barca et al., 2020; Borghi et al., 2019; Connell & Lynott, 2013; De Deyne et al., 2019; Günther et al., 2020; Louwerse et al., 2015; Santos et al., 2011; Siakaluk et al., 2008; Wingfield & Connell, 2019). This study investigates the interplay between linguistic and embodied information as a function of stimulus-bound and participant-bound variables. For this purpose, we will analyse data from the Calgary Semantic Decision project, including the participants' vocabulary size (Pexman et al., 2017; Pexman & Yap, 2018), together with further variables corresponding to linguistic information—namely, word co-occurrence (Wingfield & Connell, 2019) and word association (De Deyne et al., 2019)—, as well as variables corresponding to embodied information—namely, perceptual and motor connotations (Lynott et al., 2019; Pexman et al., 2019) and emotional information (Warriner et al., 2013). Below, we review the background literature, before outlining the method, comprising the variables used, the research questions, hypotheses and tests, and further details about the statistical procedure.

Background

Linguistic information refers to people's knowledge of distributional language statistics—that is, the common associations among words. These associations, which can be of varying strength, are acquired through language use (Barca et al., 2020; Bullinaria & Levy, 2007, 2012; Dove, 2019; Firth, 1957; Landauer & Dumais, 1997; Lenci, 2018; Ponari, Norbury, Rotaru, et al., 2018; Ponari, Norbury, & Vigliocco, 2018, 2020; Vigliocco et al., 2018). Different types of linguistic information exist (Vankrunkelsven et al., 2018), including word co-occurrence (Winfield & Connell, 2019) and word association (De Deyne et al., 2019).

Embodied information refers to the experience associated with concepts besides word context associations. Different types of embodied information exist; notably, perceptual, motor, emotional and social (Barsalou, 1999; Borghi et al., 2019; Kousta et al., 2011; Pulvermüller, 1999; Vigliocco et al., 2009). For instance, using a word recognition paradigm known as the conceptual modality switch, studies have found that switching across concepts in different dominant modalities (e.g., auditory, haptic, visual…) incurs a processing cost measurable throughout the time course of semantic processing, demonstrating the role of modality-specific systems (Bernabeu et al., 2017).

Linguistic and embodied information are intertwined. For instance, the embodied grounding of words need not be based on direct personal experience, as language encodes some of the embodied information. Part of the meaning of words, including sensorimotor and emotional connotations, can be bootstrapped based on the usual distribution of words (Bestgen & Vincze, 2012; Bruni et al., 2014; Chersoni et al., 2020; Günther et al., 2019; Günther et al., 2020; Lenci et al., 2018; Mandera et al., 2015; Recchia & Louwerse, 2015; Snefjella & Kuperman, 2016; Snefjella et al., 2020; Vankrunkelsven et al., 2015; Vankrunkelsven et al., 2018). In this regard, the embodied experience that is encoded in language can serve as a shortcut during semantic processing, which is useful because linguistic distributional information becomes available more quickly than sensorimotor information (Connell, 2018; Connell & Lynott, 2013; Louwerse & Connell, 2011; Louwerse et al., 2015).

Word concreteness in conceptual processing

The interplay between linguistic and embodied information is systematically influenced by several variables, such as word concreteness (Barca et al., 2020; Borghi, 2020; Borghi et al., 2019; Dove, 2016; Kousta et al., 2011; Montefinese et al., 2020; Pexman et al., 2017; Pexman & Yap, 2018; Vigliocco et al., 2014; Wingfield & Connell, 2019). For instance, the processing of relatively concrete words, compared to that of more abstract words, has been found to rely especially on sensorimotor information (Kousta et al., 2011; Vigliocco et al., 2014). In contrast, the processing of relatively abstract words tends to rely more heavily on linguistic (Barca et al., 2020; Snefjella & Kuperman, 2016; Snefjella et al., 2020), social (Borghi et al., 2019) and emotional information (Kousta et al., 2011; Ponari, Norbury, Rotaru, et al., 2018; Ponari, Norbury, & Vigliocco, 2018, 2020; Vigliocco et al., 2014). Caveating the former background regarding the role of language, however, Ponari, Norbury, Rotaru, et al. (2018) found that the learning and processing of relatively abstract words did not rely on linguistic distributional processing more than did the learning of concrete words. Thus, the authors encouraged examining the roles of emotional and social information in the grounding of abstract words. In another caveat to the above background, Harpaintner et al. (2020) found that the processing of relatively abstract words consistently did rely on motor and perceptual (especially visual) information, to a similar degree as the processing of concrete concepts would (see also Kiefer & Harpaintner, 2020; Moseley et al., 2012). In conclusion, the details behind the processing of abstract and concrete concepts still warrant further research.

As a general acknowledgement, it may be relevant to note that the distinction between concrete and abstract concepts, however enduring and prolific, may not always yield the greatest precision (Barsalou et al., 2018; Borghi et al., 2018; Connell & Lynott, 2012; Desai et al., 2018; Günther et al., 2020; Muraki et al., 2020).

Interplay between linguistic and embodied processing

The relative importance of linguistic and embodied information can be influenced by stimulus-centred variables such as the properties of words (Pexman et al., 2017), by individual differences (Pexman & Yap, 2018), and by task-centred variables such as depth of processing (Connell & Lynott, 2013; Pexman et al., 2019). In the present study, we investigate the linguistic-embodied interplay using data from the Calgary Semantic Decision task (Pexman et al., 2017). In this task, participants judged whether a series of words related to abstract or concrete entities. We analyse the dependent variable of response times, leaving response accuracy aside as it is susceptible to not-so-clear influences (Pexman & Yap, 2018). The Calgary data set also includes a measure of word concreteness (Brysbaert et al., 2014) and a measure of individual differences in vocabulary size (Pexman & Yap, 2018). To examine a set of confirmatory research questions, we will extend this data even further by including measures of linguistic information (De Deyne et al., 2019; Wingfield & Connell, 2019) and embodied information (Lynott et al., 2019; Pexman et al., 2019;

Warriner et al., 2013). Below, we detail the characteristics of the variables, the research questions and hypotheses, and the statistical analyses.

Variables

All the variables used are described below. As detailed, some of the variables will only be considered in preselections among various candidates. Further below, the research questions detail the purpose of each variable.

Dependent variable

The dependent variable is made of response times from Pexman et al.'s (2017) semantic decision task. Following Pexman et al., incorrect trials (i.e., 12.49% in Pexman et al.) will be removed. Moreover, trials faster than 250 ms (i.e., 0.02 % in Pexman et al.) or slower than 3,000 ms (i.e., the timeout point; 0.49 % in Pexman et al.) will also be removed. While Pexman et al. went on to remove outlier trials accounting for a further 1.37% of the responses, we will follow statistical advice to keep these outliers and perform a robust model (detailed below).

Independent variables

The independent variables are determined by the research questions (detailed below). Each IV is a single variable. In some cases, as specified, a pretest is performed to select one variable out of several options.

- **IV-1. Participant's vocabulary size (`vocabulary_size`):** from Pexman and Yap (2018)

- **IV-2. Participant's gender (`participant_gender`):** from Pexman and Yap (2018)

- **IV-3. Word concreteness (`word_concreteness`):** a binary factor extracted from the Calgary Semantic Decision data (Pexman et al., 2017; original norms from Brysbaert et al., 2014). The distribution of the variable from Pexman et al. is bimodal, comprising one side of abstract words (concreteness values between 1.04 and 2.08) and another side of concrete words (concreteness values between 3.78 and 5). This bimodality is frequent (Bonin et al., 2018). In previous studies, the abstract and concrete sets of words were separately analysed (Pexman et al., 2017; Pexman & Yap, 2018). We will instead analyse these sets together, by implementing concreteness as a variable, in order to analyse the interaction between concreteness and other variables, which is central to our research questions (below). Concreteness will be a continuous variable, unless the bimodal distribution of this variable interferes with the distribution of the residuals (Schielzeth et al., 2020), in which case the variable would be turned into a binary factor (i.e., abstract / concrete).

The next two variables contribute to the linguistic system. Two different types of linguistic information are used, namely, word co-occurrence and word association. Both variables are based on concreteness ratings by participants, and both are likely to be relevant to word concreteness and semantic decision (De Deyne et al., 2019; Vankrunkelsven et al., 2018; Wingfield & Connell, 2019). Similar cases of related but distinct variables include concreteness and word frequency (Kousta et al., 2011), arousal and valence (Citron et al., 2014a; Kuperman et al., 2014; Snefjella & Kuperman, 2016; Vigliocco et al., 2014), and perception and action (Andrews et al., 2014). The inclusion of both variables has a twofold purpose. Firstly, studying word co-occurrence and word association allows the comparison of different models within the linguistic system, contributing to a theoretical expansion beyond the linguistic-versus-embodied dichotomy. A comparison between word co-occurrence and word association found that both types were equally good at predicting Brysbaert et al.’s (2014) concreteness ratings (Vankrunkelsven et al., 2018). More generally, several models—which could correspond to compatible subsystems—exist within the linguistic system, including word-to-word associations of varying complexity (Wingfield & Connell, 2019). Secondly, the inclusion of two similar but distinct variables—i.e., word co-occurrence and word association—will add robustness to our conclusions, amid challenges to the robustness of corpus-based approximations to norms such as concreteness (Snefjella & Blank, 2020). Since both variables are primarily framed within the linguistic system, rather than the embodied system, they can provide convergent evidence to support the hypothesised role of linguistic knowledge. Thus, the analyses of both variables can serve to reinforce the overall hypothesis about the linguistic system, or to caveat it. For instance, under a hypothesis that predicted a similar effect for both word co-occurrence and word association, if the results only yielded a significant effect for one of the variables, we would conclude that further research is necessary. Consequently, in future studies, the nonsignificant variable could be detached from the linguistic system, or the overall hypothesis could be reconsidered. Further details about each variable are specified below.

- **IV-4. Word co-occurrence (**`word_cooccurrence`**):** a linguistic distributional distance measure based on word co-occurrence, from Wingfield and Connell (2019; see also Bullinaria & Levy, 2007, 2012). In the semantic decision study in Wingfield and Connell (2019)—Study 5 in the current preprint—, the effects of multiple lexicosemantic variables were examined based on Pexman et al.'s (2017) semantic decision task. This task required an *Abstract* or *Concrete* response to each stimulus word. The variables that best predicted response times were measures reflecting the distance from each stimulus word to two labels that were central to the task, namely, the words 'abstract' and 'concrete'. Wingfield and Connell studies this distance measure in various forms, such as Euclidean, cosine and correlation. Cosine and correlation distance yielded similar results. Since the authors note that correlation distance has been recommended over cosine distance (Kiela & Clark, 2014), we will use the correlation distance variable.

Preselection of one variable

To analyse the interaction of word co-occurrence with other variables, we need to operationalise it as a single variable, rather than two. For this purpose, we will select one variable out of the options below, by comparing the effect of each variable on the semantic decision RT.

- Distance from stimulus word to word 'abstract' (Wingfield & Connell, 2019)
- Distance from stimulus word to word 'concrete' (Wingfield & Connell, 2019)
- A difference score computed by subtracting the distance to 'abstract' from the distance to 'concrete' (based on Wingfield & Connell, 2019)

Each of the three variables above will be tested in a separate model, which is necessary because the zero-order correlations among these variables are close to $r = 1$ (Wingfield & Connell, 2019; see Dormann et al., 2013; Harrison et al., 2018). The variable that produces the largest effect on RTs will be used to represent word co-occurrence.

- **IV-5. Word association (**`word_association`**):** a spreading-activation measure based on the concreteness (Brysbaert et al., 2014) of the three words that are most commonly associated with each stimulus word (for a rationale about word association, see Buchanan et al., 2001; Duñabeitia et al., 2008; Reilly & Desai, 2017). Such a method is supported by Snefjella and Kuperman (2016), who compared the influence of emotional and sensorimotor properties of words with the influence of such properties in associated words, across tasks. The authors found that the properties of the associated words always explained unique variance. In some tasks, the associates even explained more variance than the words themselves (see also Snefjella et al., 2020). In our study, the associated words will be obtained from the "Small World of Words" norms ('R_{123}' measure; De Deyne et al., 2019). De Deyne et al. validated their word association norms using the same semantic decision data that we are using (Pexman et al., 2017), and found that word association was important in the semantic decision task, even more than word frequency (see also Vankrunkelsven et al., 2015; Vankrunkelsven et al., 2018). The concreteness norms we will use (Brysbaert et al., 2014) were collected from participants who rated the words from abstract to concrete on a 5-point scale (cf. the abstract/concrete choice in Pexman et al., 2017, which was the basis for the word co-occurrence measures used for IV-3, above).

The next four variables—like all others in this study—are determined by the research questions (see section below). This note should help avoid any confusion about the overlap among these variables (each further described below). Firstly, IV-6 captures embodied information as a single unit. To create it, one variable will be selected out of several options encompassing sensorimotor and emotional information. Our research questions also require a sensorimotor variable, and two types of emotional information (IV-7), namely arousal (IV-8) and valence (IV-9). Since the latter variables will be part of the preselection for IV-6, we will ensure not to duplicate any variable using different names. For this purpose, the name of IV-6 will specify the original source as a suffix—i.e., `embodied_sensorimotor` or `embodied_arousal` or `embodied_valence`. Then, among IV-7, IV-8 and IV-9, the variable that was already selected for IV-6 will not be duplicated. For instance, if the variable selected for IV-6 turned out to be sensorimotor, we would not include a redundant IV-7 (`sensorimotor`) in the final model.

- **IV-6. Embodied information:** one variable selected from several options (to be called `embodied_sensorimotor` or `embodied_arousal` or `embodied_valence`).

  The various sources of embodied information—e.g., perceptual, motor and emotional—interact. For instance, perceptual and motor information appear to be more important for the processing of relatively concrete words, whereas emotional information tends to be more important for the processing of relatively abstract words (Kousta et al., 2011; Moffat et al., 2015; Newcombe et al., 2012; Ponari, Norbury, Rotaru, et al., 2018; Ponari, Norbury, & Vigliocco, 2018, 2020; Vigliocco et al., 2014).

  Preselection of one variable

  To analyse the interaction of embodied information with other variables, we need to operationalise it as a single variable. For this purpose, we will select one variable out of the following options, by comparing the effect of each variable on the semantic decision RT.

  - Body-Object Interaction rating (Pexman et al., 2019; see also Siakaluk et al., 2008)

  - Variables from the Lancaster Sensorimotor Norms (Lynott et al., 2019), namely:

    1. Auditory.mean
    2. Gustatory.mean
    3. Haptic.mean
    4. Interoceptive.mean
    5. Olfactory.mean
    6. Visual.mean
    7. Foot_leg.mean

8. Hand_arm.mean
9. Head.mean
10. Mouth.mean
11. Torso.mean
12. Max_strength.perceptual
13. Minkowski3.perceptual
14. Exclusivity.perceptual
15. Dominant.perceptual
16. Max_strength.action
17. Minkowski3.action
18. Exclusivity.action
19. Dominant.action
20. Max_strength.sensorimotor
21. Minkowski3.sensorimotor
22. Exclusivity.sensorimotor
23. Dominant.sensorimotor

- Arousal, from Warriner et al. (2013)
- Valence, from Warriner et al. (2013)

According to the literature, these variables are theoretically and statistically distinguishable. Regarding the latter, the highest correlations may be that between concreteness and body-object interaction, r = .75 (Pexman et al., 2019; see also Connell & Lynott, 2012), and that between concreteness and word association, which could be around r = .7 (see Table 3 in Snefjella & Kuperman, 2016, but also note that said study used text-based associations whereas we will use normed associations from human ratings).

The variable that produces the largest, significant effect, based on the standardised regression coefficient (β), will be used to represent embodied information. In this preselection model, no interactions among the relevant variables will be set, as main effects are not reliable when the same variables are present in interactions (Crawford et al., 2014; Kam & Franzese, 2007; Hayes et al., 2012).

- **IV-7. Sensorimotor information (`sensorimotor`):** one variable out of various options. In case that the variable selected for IV-6 were sensorimotor (thus called `embodied_sensorimotor`), no redundant `sensorimotor` variable would be used.

    A sensorimotor (perceptual or motor) variable is needed for Research question G. Thus, in case that the IV-6 did not turn out to be a perceptual or motor variable (instead being arousal or valence), a sensorimotor variable would be selected by following a preselection similar to that done for IV-6, but without arousal and valence.

The next two variables correspond to emotional information (Citron et al., 2014a, 2014b; Kousta et al., 2009; Kousta et al., 2011; Kuperman et al., 2014; Lenci et al., 2018; Montefinese, 2019; Montefinese et al., 2020; Moffat et al., 2015; Newcombe et al., 2012; Ponari, Norbury, Rotaru, et al., 2018; Ponari, Norbury, & Vigliocco, 2018, 2020; Vigliocco et al., 2018; Yao et al., 2016).

- **IV-8. Arousal (`arousal`):** from Warriner et al. (2013). In case that the variable selected for IV-6 were arousal (thus called `embodied_arousal`), no redundant `arousal` variable would be used.

- **IV-9. Valence (`valence`):** from Warriner et al. (2013). In case that the variable selected for IV-6 were sensorimotor (thus called `embodied_valence`), no redundant `valence` variable would be used.

Research questions, hypotheses and statistical tests

For the nine research questions (RQ)—labelled from A to I—, the dependent variable is response time from Pexman et al.'s (2017) semantic decision task. The values of reference are the standardised regression coefficient (β) and the corresponding *p* value. All the hypotheses are directional and based on the literature. For each research question, a hypothesis and a statistical test are provided (structure inspired by a preregistration template by Sara J. Weston and Marjan Bakker, available at https://osf.io/zpfnb/.).

RQ-A. The importance of linguistic and sensorimotor information

Research on conceptual processing since the late 1990s has revealed two plausible systems, or models: a linguistic one and a sensorimotor one (for reviews, see Andrews et al., 2014; Barsalou, 2016; Mahon & Caramazza, 2008; Mahon & Hickok, 2016). These systems appear to be modulated by contextual variables, such as depth of lexicosemantic processing (Connell & Lynott, 2013) and individual differences such as spatial cognition preferences (Vukovic & Williams, 2015), reading ability (Yap et al., 2012) and vocabulary size (Pexman & Yap, 2018). Notwithstanding the modulating variables, we can try to gauge the unique effects of linguistic and sensorimotor information.

- **Hypothesis.** Since the literature does not warrant a definite hypothesis, we acknowledge both the hypotheses available. On the one hand, in line with embodiment theories of conceptual processing, embodied information may have a larger effect on semantic decision RT than linguistic information (Andrews et al., 2014; Barsalou, 2016). On the other hand, in line with amodal theories of conceptual processing, linguistic information may have a larger effect on semantic decision RT than does embodied information (Mahon & Caramazza, 2008; Mahon & Hickok, 2016). Regarding linguistic information, the same pattern should present for word co-occurrence and word association separately (Vankrunkelsven et al., 2018).

- **Statistical test A.1:** Main effects of word co-occurrence and embodied information. In this model, we do not include the interaction between the two target variables, as main effects are not reliable when the same variables are present in interactions (Crawford et al., 2014; Kam & Franzese, 2007; Hayes et al., 2012). Indeed, packages facilitating marginal effects, such as 'emmeans' (Lenth, 2018), warn about this.

- **Statistical test A.2:** As above but using word association instead of co-occurrence.

RQ-B. The contribution of linguistic information

Research in psycholinguistics has suggested that conceptual processing can be supported by semantic information derived from the common distribution of words in a language—hereby dubbed linguistic information (De Deyne et al., 2019; Günther et al., 2020; Louwerse et al., 2015; Snefjella & Kuperman, 2016; Snefjella et al., 2020). The data we are analysing provides an opportunity to test whether linguistic information contributes to semantic decision over and above word concreteness. We will examine this question using linguistic information in two variants, namely, word co-occurrence and word association (defined above; see also Study 5 in Wingfield & Connell, 2019, using the Calgary semantic decision data; Vankrunkelsven et al., 2018).

- **Hypothesis.** Linguistic information (in its two variants) is a significant predictor of RT over and above word concreteness (De Deyne et al., 2019; Günther et al., 2020; Louwerse et al., 2015; Snefjella & Kuperman, 2016; Snefjella et al., 2020). Specifically, two significant interactions are expected: word co-occurrence by concreteness, and word association by concreteness.

    - **Statistical test:** Main effects of word co-occurrence and word association, while controlling for concreteness and for the three-way interaction among these variables. This test is done in the full model (see Statistical procedure).

RQ-C. Word co-occurrence and word association

Word co-occurrence and word association are two different means of representing linguistic information. Word co-occurrence is based on the distance between words in a corpus (e.g., between 'cat' and 'abstract'; see Study 5 in Wingfield & Connell, 2019, using the Calgary semantic decision data), whereas word association is based on human-produced associations for cue words (for instance, 'fur' for the cue 'cat'; see De Deyne et al., 2019). While research does not always distinguish between types of linguistic distributional information, the comparison may be worthwhile. Vankrunkelsven et al. (2018) analysed results from a continued free word association task and found that word association tended to be more efficient than word co-occurrence at predicting lexical variables—i.e., age of acquisition—and emotional information variables—i.e., valence, arousal and dominance. Yet, interestingly, when word concreteness was predicted, the authors found that word co-occurrence and word association were equally good predictors (see also Vankrunkelsven et al., 2015). In another relevant study, De Deyne et al. (2019) validated their word association norms using the same semantic decision data that we are using (Pexman et al., 2017), and found that word association was important in the semantic decision task, even more than word frequency. These corpus-focussed and task-focussed precedents pave the way for a comparison of word co-occurrence and word association in semantic decision.

- **Hypothesis.** Following Vankrunkelsven et al. (2018), we hypothesise that both word co-occurrence and word association play significant roles in semantic decision.

    - **Statistical test:** Effects of word co-occurrence and word association in a model including main effects of each and interactions between them. The involvement of both variables in significant main effects or interaction effects would confirm the above hypothesis. Since the literature does not warrant specific hypotheses for each of these tests independently, the *p* values will be corrected to prevent inflating the family-wise error rate. The Bonferroni method will be used; namely, multiplying each *p* value that is considered for this research question by the total number of these *p* values (Armstrong, 2014). This test is done in the full model (see Statistical procedure).

RQ-D. Role of vocabulary size in the interplay between linguistic and embodied information

Some people know more words than others. However, differences in vocabulary size don't seem to dramatically impact individuals, as people with smaller vocabularies can understand language well-enough to complete most tasks. Considering the availability of linguistic and embodied information, the possibility exists that participants with smaller vocabularies compensate by relying more heavily on embodied processing compared to participants with larger vocabularies. From a simpler but converging perspective, we hypothesise that larger-vocabulary participants possess faster access to the linguistic system, compared to smaller-vocabulary participants.

- **Hypothesis.** Higher vocabulary size predicts greater reliance on linguistic information than on embodied information.
    - **Statistical test:** Interaction of vocabulary size, linguistic information (in its two variants) and embodied information. The necessary lower-order interactions will be analysed to investigate the directional effects in the hypothesis. This test is done in the full model (see Statistical procedure).

RQ-E. The role of participant gender in the interplay between linguistic and embodied information

Some research has suggested that women have an advantage for language (Burman et al., 2008; Jung et al., 2019; Ullman et al., 2008).

- **Hypothesis.** Linguistic information (in its two variants) has a greater importance (reflected in a significantly larger effect size) in female than male participants, in accord with research showing advantages for females across areas of language learning and use (Burman et al., 2008; Jung et al., 2019; Ullman et al., 2008).
    - **Statistical test:** Interaction of linguistic information (in its two variants) and participant gender. This test is done in the full model (see Statistical procedure).

RQ-F. The role of word concreteness in the interplay between linguistic and embodied information

When comparing the importance of linguistic and embodied information, we can consider the degree of concreteness of the words being processed (Barsalou, 1999; Paivio, 1986; Pulvermüller, 1999; for a review, see Bolognesi & Steen, 2018). Borghi et al. (2019) review evidence suggesting that linguistic information is particularly relevant when processing relatively abstract words (e.g., *spirit, existence*), because these words are weakly attached to the physical world, compared to concrete words (Paivio, 1986; Welcome et al., 2011). In contrast, when processing relatively concrete words (e.g., *music, terrace*), embodied information is likely to be more useful (Barca et al., 2020; Duñabeitia et al., 2009). Such concreteness-dependent flexibility is akin to the depth-dependent flexibility found in other studies, whereby relatively shallower tasks (e.g., sensibility judgement) and relatively fast responses were related to more linguistic bootstrapping, that is, word-to-word associations in conceptual processing. In contrast, relatively deeper tasks (e.g., property generation) and slower responses were related to more perceptual simulation (Connell & Lynott, 2013; Louwerse & Connell, 2011; Santos et al., 2011).

- **Hypothesis.** Linguistic information is more important (reflected in a significantly larger effect size) than sensorimotor information for processing relatively abstract words. In contrast, when processing relatively concrete words, linguistic and sensorimotor information have more similar importance (Borghi et al., 2019).

    - **Statistical test:** Interaction of word concreteness, linguistic information (in its two variants) and sensorimotor information. The necessary lower-order interactions will be analysed to investigate the directional effects in the hypothesis. This test is done in the full model (see Statistical procedure).

RQ-G. The role of word concreteness in the interplay between sensorimotor and emotional information

In word recognition, important differences appear between relatively abstract and relatively concrete words (Barber et al., 2013; Binder et al., 2005; Dove, 2016; Kousta et al., 2009). For instance, perceptual and motor information is especially relevant for the processing of concrete words, whereas emotion is more relevant for abstract words. This interaction has appeared in the context of various tasks, such as semantic decision (Moffat et al., 2015; Newcombe et al., 2012), lexical decision (Kousta et al., 2011; Ponari, Norbury, Rotaru, et al., 2018; Ponari, Norbury, & Vigliocco, 2018, 2020; Vigliocco et al., 2014), naming (Moffat et al., 2015) and concept definition (Ponari, Norbury, & Vigliocco, 2018, 2020). The current study will draw on Pexman et al.'s (2017) semantic decision data.

Two indices representing emotional information, namely arousal and valence, have been found to be important in conceptual processing (Citron et al., 2014b; Kousta et al., 2011; Kuperman et al., 2014; Snefjella & Kuperman, 2016; Vigliocco et al., 2014; Yao et al., 2016; but see also Kousta et al., 2009).

- **Hypothesis.** Following the above literature, we hypothesise that perceptual or motor information will be especially relevant for the processing of concrete words, whereas emotion will be more relevant for abstract words. Moreover, regarding emotion, we follow the predominant evidence, and thus hypothesise that both arousal and valence will present the aforementioned effect in the same direction.

  - **Statistical test:** A three-way interaction of word concreteness, sensorimotor information and arousal, and a three-way interaction of word concreteness, sensorimotor information and valence. This test is done in the full model (see Statistical procedure).

RQ-H. The relationship between word concreteness and linguistic information

It has been posited that linguistic information is more important when processing abstract rather than concrete words (Borghi et al., 2019; see also Andrews et al., 2009, 2014). However, this interaction was questioned by Ponari, Norbury, Rotaru, et al. (2018), who found that linguistic information was *not* particularly important for the learning and processing of relatively abstract concepts, compared to more concrete ones.

- **Hypothesis.** Since the literature does not warrant a definite hypothesis, we acknowledge both the hypotheses available. If linguistic information is indeed more important for the processing of abstract words, rather than concrete ones, we should find a significant interaction of linguistic information and concreteness displaying the aforementioned direction. Otherwise, this interaction in the aforementioned direction should not be significant.

    - **Statistical test:** Interaction of linguistic information and word concreteness. This test is done in the full model (see Statistical procedure).

RQ-I. The interactive roles of word concreteness and vocabulary size in the interplay between linguistic and embodied information

Higher vocabulary size predicts greater attention to the more relevant sources of information (Pexman & Yap, 2018). In this sense, having a larger vocabulary would bring along the advantage of a more efficient performance in conceptual processing. The literature presents two divergent hypotheses depending on the relevance of linguistic information for abstract versus concrete words.

- **Hypothesis.** Since the literature does not warrant a definite hypothesis, we acknowledge both the hypotheses available. If we assume that linguistic information is generally more relevant when processing relatively abstract rather than concrete words (Borghi et al., 2019), participants with a higher vocabulary size should pay more attention to linguistic than embodied information in their responses to the more abstract words. Alternatively, if we assume that linguistic information is not more important for learning, and thus processing, abstract words, compared to concrete ones (Ponari, Norbury, Rotaru, et al., 2018), participants with varying vocabulary sizes should pay similar attention to linguistic and embodied information regardless of the degree of concreteness of words.

- **Statistical test:** Interaction of word concreteness, vocabulary size, linguistic information (in its two variants) and embodied information. The necessary lower-order interactions will be analysed to investigate the directional effects in the hypothesis. This test is done in the full model (see Statistical procedure).

For the current data set, we do not have measures of individual differences related to embodied processing. Yet, including such measures in future studies, to examine the relative roles of linguistic and embodied information, could be valuable (e.g., Vukovic & Williams, 2015). The same applies to individual differences related to intelligence quotient, as it is known to correlate considerably with vocabulary size (Ratcliff et al., 2010; see also James et al., 2018; Pexman & Yap, 2018).

Statistical procedure

The statistical analysis will be based on Frequentist, linear mixed-effects models.

Standardisation of predictors

All continuous predictors will be standardised—i.e., centred and scaled—to mitigate any collinearity, and to facilitate model convergence as well as the interpretability of the results (Harrison et al., 2018; Schielzeth, 2010).

Examining collinearity of predictors

Collinearity between predictors will be assessed following Harrison et al. (2018; see also Dormann et al., 2013). The following thresholds would be regarded as red flags, leading to the removal of any affected variables.

1. Zero-order correlation between any two variables of $r > .7$
2. Variance inflation factor > 10 for any predictor

Random effects

First, a maximal random effects structure will be created by including, for every fixed effect, random intercepts, random slopes and interactions among random effects parameters (Barr et al., 2013; Brown, 2020; Brauer & Curtin, 2017; Meteyard & Davies, 2020; Singmann & Kellen, 2019). If required to allow model convergence, the random effects structure will be parsimoniously lightened by firstly removing the less important parameters to avoid increasing the Type I error rate. Specifically, the gradual steps recommended by Brauer and Curtin (2017) in Table 17 will be applied in the same order (for similar advice, see Brown, 2020; Singmann & Kellen, 2019).[1] Crucially, this progressive lightening will be done for each research question separately, as the nature of the random effects that we can surrender is different in each. For instance, in those research questions that focus on three-way interactions, the random effects for any main effects and two-way interactions could be removed if required to allow convergence (Barr, 2013; Brauer & Curtin, 2017).

Fixed effects

A Satterthwaite approximation of degrees of freedom will be used to compute two-tailed p values (Luke, 2017; see also Brauer & Curtin, 2017; Singmann & Kellen, 2019). Raw effect sizes,

[1] It may be noted that maximal models can be over-conservative, which led to the proposal of a 'model selection' approach whereby random effects are *incrementally* tested, and only added to the model if they increase the explained variance (Matuschek et al., 2017). Nonetheless, we will use the standard maximal approach as it appears to be better supported for now (Brauer & Curtin, 2017; Singmann & Kellen, 2019).

such as *b* and *F*, and the standardised effect size β will be reported (Lorah, 2018). The order of events will be as follows:

1. Creation of a basic lexical model based on the five variables below and their interactions, which were also used in Wingfield & Connell's (2019) reanalysis of the Calgary semantic decision data (original measures from Balota et al.'s 2007 corpus).

    - length in letters
    - number of syllables
    - log word frequency LgSUBTLWF
    - orthographic Levenshtein distance OLD20
    - phonological Levenshtein distance PLD20

    First, a selection will be carried out including main effects and interactions among all variables. Significant main effects and interactions will be retained hereafter.

2. Preselection of one embodied information variable (IV-6).

2.1. If the variable selected in the previous step turns out to be either arousal or valence, a sensorimotor variable will be selected in this step (IV-7). Otherwise, this step will not apply.

3. Main-effects-only model for Research question A.

4. Full model for Research questions B to I.

Procedure in case of abnormally distributed residuals

In each model, the distribution of the residuals will be visually examined using detrended quantile-quantile (Q-Q) plots (Loy et al., 2016), created with the `qqplotr` package (Almeida et al., 2017). Wherever the residuals are not normally distributed, a method will first be applied that aims to reduce the influence of outliers and the imprecision of parameters, while preserving the interpretability of parameters (Lo & Andrews, 2015). In an alternative to the typical transformation of the dependent variable (Balota et al., 2013), Lo and Andrews (2015) adjusted the model instead, specifically using an Inverse Gaussian generalised linear mixed-effects model (GLMM) with identity link function. The authors found that this method yielded more interpretable results and increased the statistical power (for an implementation in R, see Holt et al., 2020; for further background, see Knief & Forstmeier, 2018; Schielzeth et al., 2020; Schramm & Rouder, 2019). Moreover, compared to transformations of the dependent variable, the GLMM method appears to be better suited to the study of individual differences (Lo & Andrews, 2015), which is convenient for our examination of vocabulary size.

Outliers

Removing outliers may bias the results (Bakker & Wicherts, 2014; Fonnesu & Kuczewski, 2019), especially if the outliers happen to belong to the distribution of interest (Leys et al., 2019). Since Pexman et al. (2017) identified some outliers (1.37% of responses), we will complement our analyses with a robust version for the purpose of comparison. This robust version will use the `rlmer` function in the `robustlmm` R package. This function uses the linear mixed model (LMM). At present, no option for GLMM appears to be available in R.[2] Thus, for any model that has to use GLMM due to non-normal residuals (as detailed above), the robust version will have to switch to LMM. In any event, it may be noted that the violation of normality has a limited influence in mixed-effects models (Schielzeth et al., 2020).

[2] For instance, see: https://community.rstudio.com/t/fit-a-mixed-effects-model-using-negative-binomial-and-also-compute-robust-standard-errors/77015.

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