# What Do We Grasp At A Glance? Investigating Conceptual Representations Through Rapid Object Categorization

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## ABSTRACT


What Do We Grasp At A Glance? Investigating Conceptual Representations Through Rapid Object Categorization

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We report on two experiments investigating the nature of conceptual tokening—whether concepts are accessed via the content of lexical labels representing whole objects or constituent conceptual properties—using a picture-word masked priming congruency task with brief exposures (50/60 ms or 190/200 ms). In Experiment 1, participants were presented with picture-word pairs and had to judge whether the stimuli were related to each other. In Experiment 2, participants completed the same task while wearing red-blue anaglyph glasses—allowing us to control for the potential overlap between retinal projections, and investigate the role of visual pathways and early posterior visual projections during object and word recognition. For each picture (e.g., a dog), one of four word probes was presented for congruency decision: the basic level category label of the picture (e.g., *dog*), a superordinate label (e.g., *animal*), a high-prototypical (e.g., *bark*), or low-prototypical feature (e.g., *fur*). Response times and accuracy to congruency decisions were analyzed through linear mixed effects models. Results showed that (a) at 50/60 ms, pictures paired with superordinate labels engendered faster and more accurate responses than those paired with high- and low-prototypical features—but no differences with basic level labels, and (b) at 190/200 ms, superordinate and basic level labels yielded faster and more accurate responses than high- and low-prototypical features. We suggest that object concepts are represented in the brain by non-decompositional abstract atomic symbols carrying information about their superordinate categories or information akin to their most generic lexical labels, not through their constituent or salient features.

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## Contribution of Authors

The present manuscript consists of two experiments. Both experiments were conceived and designed by Caitlyn Antal and Dr. Roberto G. de Almeida. Caitlyn created the materials, programmed the experiment, coordinated data collection with Kyan Salehi, conducted the statistical analyses, and wrote the initial draft. The final manuscript includes revisions from Dr. de Almeida. All of this work was conducted under the supervision and guidance of Dr. de Almeida.

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What Do We Grasp At A Glance? Investigating Conceptual Representations Through Rapid Object Categorization

How do we understand what we see? Given the ubiquity of our visual experiences, the complexity of the mental machinery that underlies our ability to interpret what we see is often taken for granted. For instance, despite variations in viewing conditions (e.g., luminance, orientation, degree of occlusion), humans effortlessly recognize and categorize objects within about 150 milliseconds (ms; VanRullen & Thorpe, 2001a, 2001b; Rousselet, Macé, & Fabre-Thorpe, 2003; Delorme, Richard, & Fabre-Thorpe, 2000; Thorpe, Fize, & Marlot, 1996). What seems clear is that visually decoding an object—that is, computing its natural-kind properties—must quickly token its stored representation, independent of its viewpoint. Similarly, categorizing an object must, at some stage of processing, also involve the tokening of an abstract, conceptual representation—one that is common to all token objects of the same category. Thus, taken together, it seems that for an object to be recognized, it needs to access its stored representation or *concept*—the basic unit of meaning in the brain (Fodor, 1998). However, the nature of the representations that enable object recognition and categorization remains unclear. That is, the underlying conceptual representations and computations that enable the process of binding information into categories of objects remain unclear. In the present paper, we report on two experiments investigating the cognitive mechanisms underlying the representation of object concepts. Specifically, we investigated two overarching questions: (1) *What* kind of information is accessed when we token object concepts: do we gain access to object concepts 'holistically', or do we gain access to their constituent conceptual properties?[1] And (2) *when* is that

[1] We use *holistically* in quotation marks because we do not refer to its meaning in the sense of Quine's (1953) holism, that is, in the sense that semantic information about a word or object

information accessed—that is, what is the time course of conceptual access for objects?

Research on the recognition and conceptualization of objects—that is, on how the meanings of objects are attained—has generally focused on two main issues: (a) the timing of recognition, with many studies suggesting a decoupling between object detection and recognition (Mack & Palmeri, 2010; 2011; 2015; Mack, Gauthier, Sadr, & Palmeri, 2008; Potter, 1976; Thorpe, Fize, & Marlot, 1996; de la Rosa, Choudhery, & Chatziastros, 2011; Bowers & Jones, 2008; Li, Zhong, Chen, & Mo, 2013—but see Grill-Spector & Kanwisher, 2005), and (b) the nature of what is recognized (Macé, Joubert, Nespoulous, & Fabre-Thorpe, 2009; Mack, Gauthier, Sadr, & Palmeri, 2008; Wu, Crouzet, Thorpe, & Fabre-Thorpe, 2015; Poncet & Fabre-Thorpe, 2014)—with some studies suggesting that we understand the nature of the basic-level exemplar (e.g., *dog*) before we recognize the superordinate category (e.g., *animal*; Murphy & Brownell, 1985; Jolicoeur, Gluck, & Kosslyn, 1984; Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976). However, the opposite pattern has also been found (Wu, Crouzet, Thorpe, & Fabre-Thorpe, 2014; Poncet & Fabre-Thorpe, 2014; Rogers & Patterson, 2007; Large, Kiss, & McMullen, 2004), that is, recognizing the superordinate category before the basic-level exemplar, in particular when responses are obtained under ultra-rapid categorization conditions (i.e., with stimulus presentations times below 30 ms; Fabre-Thorpe et al., 2003; Thorpe, Fize, & Marlot, 1996; Macé et al., 2009; VanRullen & Thorpe, 2001a, 2001b). Additionally, other studies have suggested that experts can categorize stimuli within their domain of expertise (e.g., bird experts) at the subordinate level (e.g., *robin*) as fast and as accurately as they can categorize it at the basic level (e.g., *bird*; Tanaka & Taylor, 1991; Johnson & Mervis, 1997), and that

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cannot be individuated. Rather, the idea that we are highlighting here is that of recognizing an object through its 'holistic essence' (e.g., shape), and not through its constituent features.

atypical members of basic-level categories can be categorized faster at the subordinate level (e.g., *penguin*) than at the basic level (Jolicoeur et al., 1984). Thus, the nature and speed of object categorization is still subject to much debate.

Beyond (a) the timing and (b) the nature of object recognition and categorization, four other issues have also been important in determining conceptual representations for objects: (c) the nature of the properties or *features* that might constitute object meanings (e.g., whether or not dogs are constituted of *fur*, *tail*, etc.; Moss, Tyler, & Taylor, 2007; Tyler et al., 2013; Martinovic, Gruber, & Müller, 2008), (d) the nature of the neuronal representation of these features in the brain (e.g., their neuroanatomical organization; Tyler et al., 2013; Clarke & Tyler, 2015; Smith et al., 2012; Martin, 2007), (e) what the patterns of semantic deficits in individuals who have suffered traumas or diseases tell us about the nature of the representation of concepts (Perri, Carlesimo, Monaco, Caltagirone, & Zannino, 2019; Mahon & Caramazza, 2009; Merck, Jonin, Laisney, Vichard, & Belliard, 2014; Hauk et al., 2007), and (f) computational models of rapid object categorization aiming to elucidate the visual features underlying rapid object recognition (Crouzet & Serre, 2011; Serre, 2016).

While some of these questions closely parallel the two overarching questions of the present study, they have been somewhat dissociated from one another. One reason for this dissociation is that many studies have employed experimental paradigms that are not well-suited for investigating the nature of object concepts at the earliest moments of conceptual tokening. For instance, some of the studies investigating the timing and nature of object recognition have employed go/no-go tasks (VanRullen & Thorpe, 2001a, 2001b; Macé, Joubert, Nespoulous, & Fabre-Thorpe, 2009; Poncet & Fabre-Thorpe, 2014), categorization tasks (Mack & Palmeri, 2010; 2015; Mack, Gauthier, Sadr, & Palmeri, 2008; Grill-Spector & Kanwisher, 2005), or saccadic choice tasks (Wu, Crouzet, Thorpe, & Fabre-Thorpe, 2014), requiring participants to make decisions based on a pre-determined criterion (e.g., whether a presented item is an instance of a *vehicle* or *animal* category). However, employing such tasks casts doubts on the validity of the results, given that participants are primed to lock into pre-determined categories. Simply put, object recognition and categorization in the real-world do not occur as a function of being explicitly told what categories to 'look for'. Rather, object categorization relies on tokening conceptual representations from amongst all of the representations stored in the conceptual system (Fodor, 1998; Fodor & Pylyshyn, 2015, Pylyshyn, 2018). Other studies have employed stimulus presentations with long duration latencies (e.g., 400-2000 ms; Rosch, 1975; Smith et al., 2012; Costa, Alario, & Caramazza, 2005; Rogers & Patterson, 2007; Wu, Crouzet, Thorpe, & Fabre-Thorpe, 2014). However, given the rapidity of the recognition system, it is thus of utmost importance that studies investigating the nature of object concepts employ research paradigms that are sensitive to the earliest stages of processing. This allows for a distinction between elucidating what kind of information arises *at the moment objects are recognized* (i.e., at the moment of concept tokening), from information that arises as a function of inferences or associations that are *triggered* by the concept, but which may not be part of the concept itself (e.g., knowing that dogs bark; Fodor, 1983; de Almeida & Antal, 2021; de Almeida & Lepore, 2018, de Almeida, 2018). Crucially, understanding what kind of information we entertain about an object requires a concerted effort—one that addresses the two questions (*what*, *when*) simultaneously, while employing research paradigms that are ecologically and externally valid as well as sensitive to the timing of perceptual encoding. Thus, tackling these problems requires deploying a combination of psychophysical methods, together with theoretical insights from areas such as vision, language, and categorization.

## Theoretical Approach

Representing two polar opposites on the nature of conceptual representations are theories that either postulate that concepts are decomposable into constituent features (e.g., the Prototype Theory: Rosch, 1973a, 1973b; Rosch, 1975; Rosch, 1978; Rosch, 1999; Rosch & Mervis, 1975; Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976; Rosch & Lloyd, 1978; Smith & Medin, 1981; Medin & Smith, 1984; Mervis & Rosch, 1981; Embodied Cognition: Barsalou, 1999, 2008; Theory-Theory: Carey, 2009) or that concepts are 'atomic' (i.e., they are not decomposable into features; e.g., Atomism; Fodor, 1998; Fodor & Pylyshyn, 2015). Prominent within the camp of decompositional theories is the Prototype Theory. According to this theory, object concepts are represented through sets of weighted features that are averaged over time. When encountering objects in the world, their salient properties (i.e., unique and essential features for concept identification or learning (Rosch, 1973a, 1973b)) are statistically weighted, their cue validities are adjusted, modifying the *prototype* (a measure of central tendency) that stands for the concept (Smith & Medin, 1981; Rosch & Mervis, 1975).[2] For instance, when encountering instances of dogs in the world, the brain records their properties, the likes of *bark*, *four-legs*, *furry*, and t*ail*. Some properties (e.g., *bark*) will be more salient and unique to dogs, whereas other properties will be highly shared across categories (e.g., *four-legs*). As such, each property is a predictive cue for a given category. Namely, the validity of a given cue *x* (e.g., *bark*) as a predictor of a given category *y* (e.g., *dog*) increases as the frequency of cue *x* occurs

[2] While it is true that Rosch (1978) states that "prototypes do not constitute a theory of representation of categories" (p. 15), she does argue that what comes to mind when we encounter the object or the word *dog* in the world is that of the prototype DOG. Thus, if what comes to mind are prototypes, and that prototypes "operate" during the classification and recognition of objects, then her theory is necessarily on the nature of concepts because the prototype is taken to be what stands in the mind for the meaning of the object or word. Ultimately, if what stands for the concept is a prototype, then her theory is a theory of concepts.

uniquely in category *y*, and decreases as the frequency of cue *x* occurs in categories other than *y*. The cue validity of a given category, then, is defined as the sum of all cue validities, for all properties, for that category (Rosch, Mervis, Gray, Johnson, & Boyes-Braem, 1976; Rosch & Lloyd, 1978; Rosch, 1999). Thus, property *x* with high cue validity for category *y* should be a better predictor for that category than property *z* with lower cue validity. Taken together, given that concepts are formed through weighting clusters of features, conceptual tokening—via both, visual and linguistic inputs—is, by hypothesis, dependent on accessing the content of these features (see Figure 1a).

Atomism, on the other hand, stands at the opposite end of the spectrum. Its main postulate is that concepts are object-based—in the sense that concepts individuate referents as a whole and not through their semantic properties—given that each individualized property in the world stands for a concept in the mind (Fodor, 1998; Fodor & Pylyshyn, 2015). According to this view, the representation of object concepts relies on a nomological mind-world relation that takes meaning representation as a link to a referent. That is, concepts are tokened through the establishment of a link obtained via object/word recognition, whereby low-level visual mechanisms (e.g., motion, edges, and figure-ground detection) individualize objects in the world. Thus, concepts are non-decompositional primitive representations that do not rely on relations to other concepts or features *by necessity*—similar to the notion that face recognition may rely on holistic processing, rather than on the computation of its parts (see Richler, Palmeri, & Gauthier, 2012; Richler & Gauthier, 2014). All other kinds of knowledge that one might have about properties related to the object (e.g., knowing that dogs *bark*) are a function of *synthetic inferences* in the form of meaning postulates (de Almeida & Antal, 2021; see Figure 1b). In other words, these relations are contingent on experience (e.g., world knowledge) rather than being necessary constituents of the concept. If these properties were to be constituents of the concept, one would need to have a criterion for determining which features are taken to be "analytic" properties bearing on the content of concepts from those that are taken to be "synthetic" or contingent on experience—see Quine (1953). But, there is no specific criterion for determining which properties are analytic and which ones are synthetic.

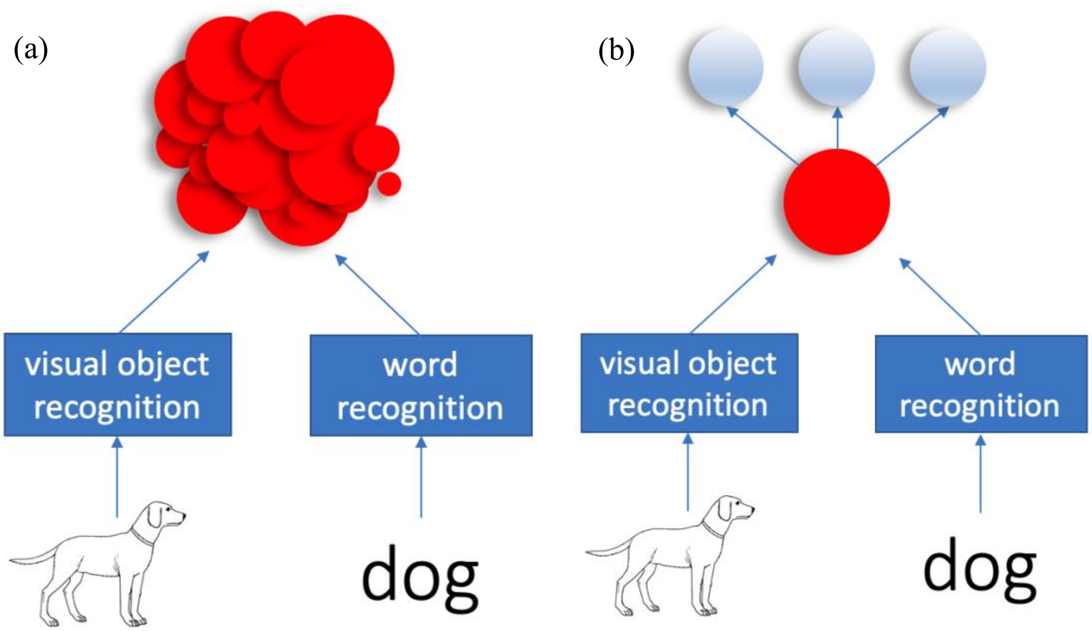


*Figure 1.* Schematic representation of conceptual tokening, according to (a) the decompositional theories, with access to concepts via features; and (b) the non-decompositional theories, with token concepts preceding inferences to other concepts ('features').[3]

[3] The circles represent different concepts/features. The sizes of the circles for the decompositional theories represent the set of features along with their associated cue validities.

The goals of the present study are set against this theoretical background: by investigating the early moments of the conceptual processes—the perceptual input of token objects—we can gain knowledge on the nature of the information that gives access to conceptual representation. It is at those early moments where the information about an object first makes contact with stored information in the conceptual system, which is at the core of other cognitive abilities.

**What is accessed when we token an object concept?**

Crucial to determining the nature of the information accessed during the retrieval of object concepts is to employ methods that are sensitive to the timing of perceptual encoding. Given the rapidity of the recognition system, it is thus of utmost importance that studies aiming to investigate the nature of object concepts employ research paradigms that are sensitive to the earliest moments cognitive processing. One such paradigm has been semantic priming (Rosch, 1975; Kahlaoui, Baccino, Joanette, Magnié, 2007; Lam, Dijkstra, & Rueschemeyer, 2015; Llyod-Jones & Humphreys, 1997), which capitalizes on the relationship between a word (e.g., the name of an object feature, such as *tail*) and an object (e.g., dog). The rationale for using semantic priming is that a prime should only facilitate a response when its semantic representation contains within it part of the mental code that is generated by the stimulus to which one must respond. For instance, if the representation triggered by a category name (e.g., *dog*) includes information about its internal structure, such as a list of properties (e.g., *bark*, *four-legs*), then responses to those properties should be facilitated by the priming of the category name. Conversely, if the representation triggered by a category name does not include internal structure, then responses should not be facilitated by the prime.

The picture-word interference (PWI) paradigm has been a prominently used method to investigate whether conceptual retrieval is facilitated or hindered by the relation between a target picture and a word prime.[4] In this paradigm, participants are instructed to name target pictures while ignoring a superimposed visual (e.g., Sailor, Brooks, Bruening, Seiger-Gardner, & Guterman, 2009; Vieth, McMahon, & Zubicaray, 2014; Caramazza & Costa, 2000; Costa, Alario, & Caramazza, 2005; Sailor & Brooks, 2014; Mahon, Costa, Peterson, Vargas, & Caramazza, 2007) or concomitantly presented auditory (e.g., Mädebach, Wöhner, Kieseler, & Jescheniak, 2017; Chen & Spence, 2018; Wöhner, Jeschenkiak, & Mädebach, 2020) distractor. While there are many variants of this paradigm, distractors are usually within-category coordinates (e.g., the word *cat* paired with the picture of a dog), category associates (e.g., the word *leash* paired with the picture of a dog), associated parts (e.g., the word *tail* paired with the picture of a dog), or unassociated parts of the picture (e.g., the word *nose* paired with the picture of a dog).

Additionally, the onset asynchronies for distractor-target pairings varies greatly across studies, with some studies presenting distractor-target pairings for one duration time (e.g., 2000 or 3000 ms; Costa, Alario, & Caramazza, 2005; Mahon, Costa, Peterson, Vargas, & Caramazza, 2007), or at various onset asynchronies, before and after the presentation of the target (Sailor & Brooks, 2014; Mädebach, Wöhner, Kieseler, & Jescheniak, 2017; Vieth, McMahon, & Zubicaray, 2014; Chen & Spence, 2018; Wöhner, Jescheniak, & Mädebach, 2020). Results typically show that participants are faster at naming target pictures (e.g., car) when they are paired with (a) distractors that are close within-category coordinates (e.g., *truck*) than distractors

[4] It is important to mention that this paradigm has been used predominantly to investigate the mechanism underlying lexical selection during spoken word production; however, the nature of the various distractor-target pairs can also be taken to elucidate the nature of object concepts.

that are far within-category coordinates (e.g., *wagon*; Mahon et al., 2007; Janssen, Schirm, Mahon, & Caramazza, 2008)—an effect known as the semantic interference effect (Lupker, 1979)—(b) category associates (e.g., *truck*) than unrelated distractors (e.g., *table*; Finkbeiner & Caramazza, 2006), or (c) associated parts to the target (e.g., *bumper*) than unrelated distractors (e.g., *parrot*; Costa, Alario, & Caramazza, 2005).

What is particularly interesting about these results in the context of the present study—and on the representation of object concepts, more broadly—is the nature of results obtained from studies employing 'associated parts to the target' as a distractor condition (e.g., the picture of a car paired with the lexical target *bumper*). While some studies suggest that naming is facilitated by distractors that are associated parts to the target object—in particular when there is a long delay between the presentation of distractor-target pairs, or when distractor-target pairs are simultaneously presented for long duration times—this effect seems to decrease over time. That is, when distractor-target pairs are simultaneously presented for short duration times (e.g., 100-300 ms; Sailor & Brooks, 2014; Mädebach, Wöhner, Kieseler, & Jescheniak, 2017—presentation times which are arguably long given that objects can be recognized following durations as short as 20 ms (VanRullen & Thorpe, 2001a)—presenting distractors that are associated parts to the target picture does not lead to a naming advantage. Rather, it leads to a semantic interference effect, that is, longer response latencies to pairs that are 'related' in comparison with those that are not. Therefore, the lack of naming facilitation for target pictures (a) when they are simultaneously presented with distractors from the 'associated parts to the target' condition, and (b) when target-'associated parts' distractor pairs are presented for short duration times—which is arguably the time point when concepts are tokened—cast doubts on the proposal that features are constituents of object representations.

Beyond these theoretical concerns, there are also several methodological issues tied to the PWI paradigm. For one, studies employing auditory stimuli do not always control for the duration of sounds (which often last between 702 and 1572 ms; Mädebach, Wöhner, Kieseler, & Jescheniak, 2017). This may lead to a greater naming advantage, in particular if the target picture was presented with a congruent sound. Additionally, for studies employing visual distractors, it is likely that the overlapping presentation of distractor-target pairs created a cluttered visual experience for participants, which may have artificially led to longer naming latencies in general. But more importantly, given the rapidity of the recognition system, it is thus of utmost importance that studies aiming to investigate the nature of object concepts employ research paradigms that are sensitive to early cognitive processes. That is, in order to properly distinguish between the kind of information represented in the core of concepts from that which arises as a function of inferences triggered by the tokening of the concept, it is of utmost importance that studies employ paradigms that (a) do not prime participants to identify or recognize predetermined categories, (b) use short presentation duration times—timepoints which are sensitive to the timing of perceptual encoding—and (c) present stimuli in a non-cluttered visual space.

**The Present Study**

In the present study, we addressed the overarching questions—*what* and *when*—in two experiments, relying on a novel psychophysical method. For both experiments, described in detail below, participants were presented with a picture-word priming congruency (PWPC) task. In this task, participants are presented with picture-word pairs and have to judge whether the items are related to each other. Pictures and target words are presented simultaneously with a 10 ms asynchrony accounting for their different recognition times: objects are presented for 50 or

190 ms, while words are presented for either 60 or 200 ms. This manipulation is crucial because repetition priming for words (e.g., dog-DOG) seems to occur minimally around 50 ms, suggesting that lexical properties—rather than letter features—are available for words within that time frame (Forster, 1999). In the case of objects, however, studies suggest that objects can be successfully categorized following presentations as short as 20-40 ms (Potter & Faulkoner, 1975; Potter, 2012, 2018; VanRullen & Thorpe, 2001a, 2001b; Thorpe, Fize, & Marlot, 1996). Given that objects seem to have faster recognition times than words, lexical stimuli are given a 10 ms advantage, over the presentation time of the pictured object. For each picture, one of four word probes is presented for congruency decision: the basic level category label of the picture (*dog*), a high-prototypical (most frequent: *bark*), a low-prototypical (less frequent: *fur*), or a superordinate feature (*animal*). Pictures are presented in the right and left visual fields. These pictures (line drawings) were taken from Snodgrass and Vanderwart's (1980) standardized set. Besides their original norms—which include naming agreement, image agreement, familiarity, and visual complexity—the 260 original pictures have been extensively normed in a study we conducted with 100 participants, yielding 78,000 features, in addition to category information, and object name (Antal & de Almeida, 2021). Given that some objects lack distinctive features (e.g., *ashtray*), for they encompass features that are shared by many objects and categories (e.g., *round*), the presentation of those features in the PWPC task might not signal strong category membership, and thus, may engender slower congruency decisions (Smith & Medin, 1981; Medin & Smith, 1984). As such, based on Antal and de Almeida's (2021) norms, cue validity

and distinctiveness values were computed for each feature, and were entered as predictors in exploratory regression analyses.[5]

We hypothesized that, if object concepts are accessed via features, high-prototypical features would yield faster response times (RTs) and greater accuracy, at both presentation timepoints, given that high-prototypical features supposedly give privileged access to concepts (e.g., *bark* for the picture of a dog). However, if object concepts are primarily accessed via labels representing the whole object, we hypothesized that category labels (e.g., dog) would yield faster RTs and greater accuracy at both presentation timepoints. Further, we predicted that prototypicality effects would only arise in the longer presentation condition (i.e., 200 ms), given that a concept first needs to be tokened before its features can be accessed.

The first experiment employed the PWPC task using stimuli displayed in black (pictures and words), whereas the second experiment presented the picture-word stimuli pairs in red and blue, while participants wore red-blue anaglyph glasses. This manipulation was introduced to avoid the potential overlap between retinal projections during early stages of processing (e.g., 1° at V1; see Pettigrew, 2001), in case there is no complete foveal split (e.g., see Lavidor & Walsh, 2004; Jordan, Paterson, Stachurski, 2008). Moreover, by using dichoptic presentation, we aimed to take advantage of binocular rivalry to understand the potential differences between

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[5] *Cue validity* was calculated by diving the sum of the production frequency for a given feature for a particular picture (e.g., *fur* for dog) by the total production frequency for that feature, across all 260 pictures (Rosch, 1978; Rosch & Mervis, 1975; Rosch & Llyod, 1978; Reed, 1972). *Distinctiveness* was defined as the inverse of the total number of pictures that a given features appears in (Tyler et al., 2013; Randall, Moss, Rodd, Greer, & Tyler, 2004; Devereux, Taylor, Randall, Geertzen, & Tyler, 2016).

hemispheric representations of word labels and objects, via ipsilateral and contralateral visual pathways and their anatomical projections.

It is well established that, during the early stages of visual processing—namely, when retinotopic information is projected onto V1—visual input is processed contralaterally: information presented in the left visual field (LVF) is processed in the right hemisphere, and information presented in the right visual field (RVF) is processed in the left hemisphere. As these hemispheric projections undergo further visual computations (i.e., from posterior areas in the visual cortex to temporal and frontal cortices), they will rely on the inter-hemispheric exchange of information, via the corpus callosum. Moreover, this early division of retinotopic projections in area V1 is said to engender processing differences, with some studies suggesting hemispheric dominance for certain classes of stimuli (e.g., words, visual objects) in early stages of processing, before full inter-hemispheric transfer takes place. For instance, it is well known that there is a strong RVF advantage for visual word recognition due to words being projected into the language-dominant left hemisphere (e.g., Finkbeiner, Almeida & Caramazza, 2006; Bub & Lewine, 1988; Hunter & Brysbaert, 2008), in particular, due to the visual word form area (VWFA)—a region in the left fusiform gyrus that has been shown to selectively respond to word forms (Cohen et al., 2000, 2002; Cohen & Dehaene, 2004). Further, while it is often difficult to dissociate "word" processing (e.g., graphemic sequences and morphological representations) from their meanings (concepts), a review of several studies contrasting meaningful versus nonmeaningful linguistic stimuli (e.g., words vs. nonwords, random words vs. sentences) found a wide cortical distribution for meaningful stimuli, primarily in the left hemisphere (Binder et al., 2009). The cortical organization of visual objects, on the other hand, seems to be more category-specific, with particular regions being dedicated to classes of visual stimuli, in both the right and left hemispheres (see Kanwisher, 2010). For instance, studies have shown that there seems to be cortical regions dedicated to the recognition of particular stimuli such as faces (e.g., Grill-Spector, Knouf, & Kanwisher, 2004), places (e.g., Epstein & Kanwisher, 1998), and body parts (Bracci, Caramazza, & Peelen, 2015). Taken together, this division in retinotopic information projected onto V1 may engender processing differences in accuracy and RTs for the processing of picture-word pairs. These hemispheric differences were manipulated in Experiment 2 aiming to understand the role of early projections in the processing of conceptual representations obtained from words and objects.

## Experiment 1: Picture-Word Masked Priming Congruency Task with Black Stimuli

### Method

#### Participants

A total of 71 participants (F = 52), between the ages of 18 and 53 (*M* = 25, *SD* = 8) were recruited from Concordia University's psychology participant pool, and from the Montreal, Ottawa, and Toronto communities through a Kijiji add. All participants were native speakers of English (i.e., learned English before the age of 5 and used it as a dominant language), had normal, or corrected-to-normal vision, no history of psychiatric or cognitive impairments, and no diagnosis of colorblindness. They were either compensated with 3 course credits or with $ 25 CAD for their participation. All participants were treated in accordance to the ethical standards adhered by Concordia University's Human Research Ethics Committee (certification number 10000023).

#### Materials

A total of 256 pictures (128 experimental and 128 fillers) were included in the study. These pictures consisted of the Snodgrass and Vanderwart (1980) line drawings with the highest naming agreement, as determined through the Antal and de Almeida (2021) norming study. Half of the pictures represented images of living things (e.g., animals, vegetables, fruits), while the other half represented images of non-living things (e.g., furniture, tools, clothing). This distinction was included for several reasons. First, living things are said to be visually more complex and more difficult to process than non-living things—in particular because living things are assumed (a) to be more similar to one-another, and (b) to encompass a larger number of features than non-living categories (Farah, McMullen, & Meyer, 1991; Moss, Tyler, & Taylor, 2007). Second, the distinction between living and non-living superordinate categories allows for generalizations across major concept categories. Third, impairments to living or non-living categories is one of the most well-documented kinds of double dissociations in cases such as Alzheimer's (e.g., de Almeida, Mobayyen, Antal, Kehayia, Nair, & Schwartz, 2021; Silveri, Daniele, Giustolisi, & Gainotti, 1991; Moss, Tyler, & Devlin, 2005; Laws et al., 2007; Whatmough & Chertkow, 2002; Zannino, Perri, Caltagirone, & Carlesimo, 2007) and brain lesions due to vascular accidents or traumas (e.g., Blundo, Ricci, & Miller, 2006; Borgo & Shallice, 2001; Capitani, Chieppa, & Laicona, 2010; Hillis & Caramazza, 1991; Massullo et al., 2012; Rosazza et al., 2003; Schweizer, Dixon, Westwood, & Piskopos, 2001). Although the present study did not investigate participants drawn from neuropsychological populations, the pattern of dissociations obtained from patients with different aetiologies suggests that the functional architecture of the unimpaired conceptual system takes living and non-living things as representing a major distinction between the representation of categories in the brain. Further, results from neuropsychological populations also suggest that the visual system may have separate subsystems, which are specialized for the recognition of living and non-living things (Farah, McMullen, & Meyer, 1991). Taken together, these major categories may engender different response patterns, thus motivating a distinction in experimental materials.

Following Snodgrass and Vanderwart's (1980) norms, the experimental pictures for living and non-living categories were matched in image agreement, $t\ (126) = 1.32$, $p = 0.19$, $d = 0.23$, 95% CI = [-0.06, 0.30], but they were not matched in visual complexity, $t\ (126) = 4.20$, $p < 0.001$, $d = 0.63$, 95% CI = [-0.95, -0.34]. Thus, visual complexity was entered as a random factor during statistical analyses.

Based on the results from Antal and de Almeida's (2021) norming study, four types of target labels were generated: (1) the category label of the picture at the basic level, (2) a high-prototypical feature, (3) a low-prototypical feature, or (4) a high-prototypical feature at the superordinate level. The lexical labels representing these types were individually presented with each picture (see examples in Table 1).

**Table 1**

*Sample lexical labels for each condition presented with the picture of a dog.*

| Label Type | Sample Target |
|---|---|
| Target Name | DOG |
| High Prototypical | BARK |
| Low Prototypical | FUR |
| Superordinate | ANIMAL |

Based on these norms, a weighted scoring system was devised to determine the target lexical labels for each category. The basic level and superordinate feature labels were taken to be the target words with the highest naming agreement (i.e., the object name most frequently listed for each picture). Specifically, for responses at the basic and superordinate levels, naming agreement was devised by dividing the number of individuals responding a given target name by the total number of participants. For instance, in response to the picture 'cat', 99 individuals responded *cat*, while one individual responded *kitty*. As such, *cat* was chosen as the target feature for the basic level and was given a naming agreement value of 0.99. The same procedure was applied to determine the target and naming agreement values for superordinate features.

A different method was employed to calculate the naming agreement of high- and low-prototypical features. Given that Antal and de Almeida's norming study required participants to list three features, using one word, for all objects presented to them, a ranked weighted response system was employed to determine the high- and low-prototypical target labels. Specifically, the feature that was listed first by a given participant received a score of 3, the second feature received a score of 2, and the last feature a score of 1. These scores were then multiplied by the number of participants responding a given feature in their ranked position. Finally, their products were summed across all ranked positions and divided by the total number of participants. This yielded the final naming agreement for a given target feature. For instance, in response to the picture 'banana', 87 individuals responded *yellow* as the first feature, 12 as the second feature, and 1 as the third feature. As such, 87 was multiplied by 3, 12 was multiplied by 2, and 1 was multiplied by 1. Their products were then summed (i.e., 286) and divided by the total number of participants (i.e., 100), for a naming agreement value of 2.86. Low-prototypical targets were determined by taking the feature corresponding to half of the naming agreement value of the high-prototypical feature. In cases where no feature precisely matched that naming agreement value, the feature with the closest lower value was taken to be the target. Furthermore, in cases of a tie between two features (i.e., those corresponding to precisely half of the naming agreement value of the high-prototypical feature), the feature that was a constituent part of the object depicted in the picture was taken to be the target.

Lastly, for all features, we then calculated cue validity and distinctiveness values. The reasoning for using these values is that, given that some objects are less associated with distinctive features (e.g., *bear*), this might engender slower responses from participants. As such, we conducted exploratory multiple regression analyses, regressing cue validity and distinctiveness values on participants' accuracy to congruency decisions (see Appendix D). Cue validity scores were devised by dividing the sum of the production frequency for a given feature for a particular picture (e.g., *fur* for the dog picture) by the total production frequency for that feature, across all 260 pictures (Rosch, 1978; Rosch & Mervis, 1975; Rosch & Llyod, 1978; Reed, 1972). Distinctiveness was defined as the inverse of the total number of pictures in which a given feature appeared (Tyler et al., 2013; Randall, Moss, Rodd, Greer, & Tyler, 2004).

Following these calculations, the 128 pictures with the highest naming agreement at the basic level were chosen as experimental items: 64 represented objects in the living category, and 64 represented objects within the non-living category. See Appendix A for the full list of experimental materials as well as the cue validity, distinctiveness, and naming agreement values associated with each picture.

In addition to obtaining lexical labels, Antal and de Almeida's norming study also allowed us to classify all lexical labels for the high and low prototypical features according to 12 properties that the labels express about the target object: dimension, quality, body-part, part-to-whole, function, temperature, substance, visual, olfactory, acoustic, tactile, and concept-association (see Table 2 for their definitions). Participants' responses on the PWPC tasks as a function of these feature classifications constitute a separate study.

**Table 2**

*Definitions for the classes of properties expressed by the features of objects.*

| Feature Subcategory | Definition |
| --- | --- |
| Dimension | Applies to measurable properties (e.g., *long* for the property of length and *small* for the property of size) |
| Quality | Applies to intrinsic (e.g., *smart* for monkey) or extrinsic properties (e.g., *soft* for bed), including aesthetical ones (e.g., *beautiful* for peacock) |
| Part-to-Whole | Parts of inanimate/non-living things (e.g., *leg* for chair) |
| Body-Part | Equivalent to 'part-to-whole' but for animate/living things (e.g., *pupil* for eye and *whisker* for tiger) |
| Function | Applies to purpose (i.e., 'telic' role; e.g., *fly* for airplane) |
| Temperature | Similar to dimension, but specific to temperature (e.g., *hot* for iron and *cold* for refrigerator) |
| Substance | What the object/thing is made of, mostly in its appearance (e.g., *fur* for bear) |
| Visual | Properties that include color and patterns (e.g., *stripes* for zebra) |
| Olfactory | Properties related to the sense of smell (e.g., *stink* for skunk) |
| Acoustic | Any reference to sound, including onomatopoeic (e.g., *purr* for cat) |
| Tactile | Any property that is tactile or related to the sense of touch (e.g., *grip* for pliers) |
| Concept-Association | Refers to relations that are none of the above, but reflect frequency of association (e.g., *water* for fish) |

**Design**

Participants were presented with the picture-word priming congruency (PWPC) task, as described in the introduction.

Experiment 1 consisted of a factorial design with 16 conditions: *presentation times* (2): 50/60 ms, 190/200 ms; *picture-word hemispheric projection* (2): left-right, right-left; and *target type* (4): basic level label, high-prototypical feature, low-prototypical feature, or superordinate feature. There were 128 experimental picture-word pairs for each of the 16 conditions, for a total of 2048 picture-word combinations. The 2048 items were counterbalanced among 16 lists, such that each list contained 8 items from the 16 conditions. Participants completed two lists, in a random sequence.

**Procedure**

Once participants were deemed eligible to participate in the experiment (i.e., they met the inclusion criteria outlined in *participants* section), they were sent a follow-up email outlining a detailed list of what their participation entailed.[6] After having carefully read the details of this email, participants indicated whether they accept to participate in the study. Furthermore, given that the second experiment required the use of anaglyph glasses (see Experiment 2, below), the glasses needed to be delivered to participants. As such, participants were required to provide a delivery address. Based on their preference and location, glasses were either mailed, or dropped off at their residence. The glasses were part of a kit containing all the necessary materials for experiment participation. In this kit, participants received: (a) the anaglyph glasses, (b) a measuring tape to measure the distance between them and their computer screen, (c) written

[6] It is important to mention that this experiment was paired with a separate, unrelated experiment. All participants completed three tasks: Experiments 1 and 2, described here, as well as the unrelated experiment. Participants completed the three experiments over the course of three days, completing one experiment per day, in a counterbalanced order.

instructions for each experiment (these were also presented on screen prior to the beginning of the experiment), and (d) general guidelines and a checklist for their participation in each task (see Appendix B). Due to the COVID-19 pandemic, the materials were not required to be returned upon completing the experiment.

Upon receiving packages, participants were then sent an email containing a link to a Qualtrics (2015) survey, as well as the individual links to each of the three tasks. The Qualtrics survey presented participants with: (a) the consent form, (b) a language background questionnaire, and (c) a computer and internet configuration questionnaire. The language background questionnaire measured participants' self-reported language history and proficiency, while the computer and internet questionnaire gathered information regarding participants' computer hardware specifications and internet resources (see Appendix C for the internet questionnaire). Given that the experiment relied on time-sensitive measures, the computer and internet configuration questionnaire provided crucial information for analyzing participants' responses by taking into account computer processing speed, memory configuration, type of operating system, monitor resolution and refresh rate, and internet speed—factors that are shown to affect stimulus presentation and data collection via online platforms (Anwyl-Irvine, Dalmaijer, Hodges, & Evershed, 2020; Bridges, Pitiot, MacAskill, & Peirce, 2020).

In each trial, participants were presented with picture-word pairs, and their task was to judge whether or not the two items are related to each other. They were instructed to complete the experiment individually, in a dimly lit room, while being seated at a viewing distance of 60 cm from the screen. Each trial consisted of the following sequence: (1) participants were prompted to press the SPACEBAR when they are ready to begin; (2) they were then presented with a centrally located fixation cross (+), for 1000 ms; (3) the presentation of the picture-word pair then appeared for either 50/60 or 190/200 ms, depending on the condition; and (4) a subsequent 100 ms backwards-mask in the form of random dots was presented (see Figure 2). The backward-mask was used to prevent visual processing beyond the presentation duration of stimuli (e.g., see Breitmeyer & Ogmen, 2000; Keysers, Xiao, Foldiak, & Perrett, 2001). Given that there was much variability in the stimuli in terms of size and complexity, the backward-mask we employed had greater spatial frequency than the stimuli. Participants were instructed to respond, as quickly and as accurately as possible, whether the pictures and words were related to each other. If so, they were instructed to press the 'yes' key, or to press 'no' otherwise. Due to the variation in participants' monitor size (*M* = 14.4 inches; *SD* = 2.70 inches; *Mode* = 13.3 inches), resolution (*M* = 2005 x 1238 pixels; *SD* = 624 x 388 pixels; *Mode* = 2560 x 1600 pixels), and refresh rate (*M* = 61 Hz; *SD* = 16 Hz; *Mode* = 60 Hz), the position of pictures and words were normalized, subtending about 3° of visual arc from the fixation cross.

The experiment began with 10 practice trials and was followed by the 128 experimental items interspersed with 128 picture-word fillers. Items were presented randomly, and no list contained more than one token item from a given experimental minimal pair. The experiment was programmed in PsychoPy3 (Peirce et al., 2019) and distributed online through Pavlovia (2020). Participants completed two lists. They were instructed to take breaks when needed, by delaying the start of the following trial (i.e., by not immediately pressing the spacebar). Without breaks, each list lasted approximately 15 minutes.

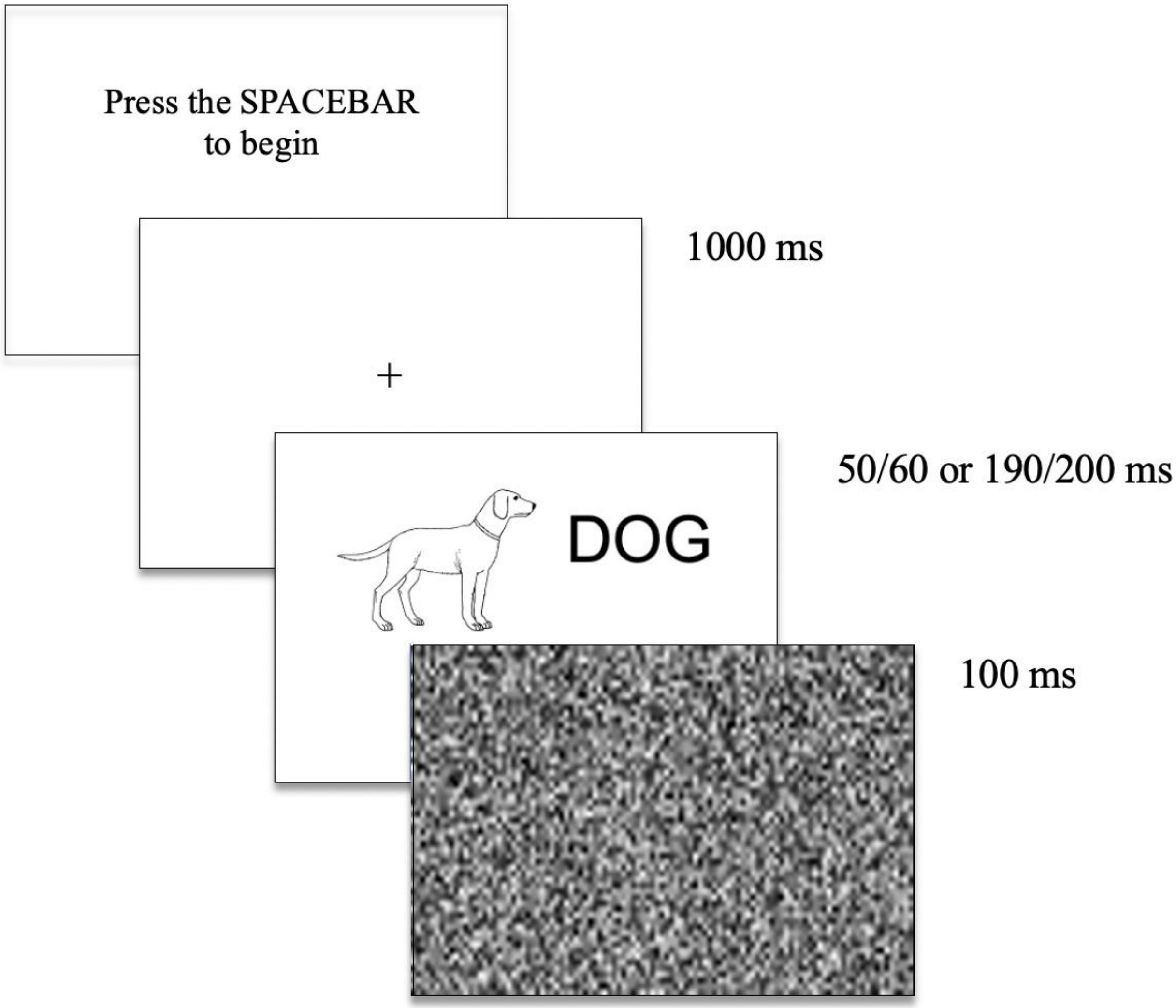


*Figure 2.* Time-course of events for each trial in the picture-word priming congruency task.

## Data Analyses

For both experiments, we conducted linear mixed effects (LME) models (Baayen, Davidson, & Bates, 2008) using the *lme4* package (Bates, Maechler, & Bolker, 2013) for the R statistical programming environment (R Dev. Core Team, 2012; 2014). For all analyses, stimulus presentation time, target type, and picture-word hemispheric projection were entered as fixed factors. Experiment 2 included the addition of a new factor: visual pathway. The models analyzed the effects of stimulus presentation time, target type, picture-word hemispheric projection, and pathway (Experiment 2), on participants' accuracy and RTs to congruency decisions. All models included random intercepts for subjects, items, target word production frequency, and visual complexity values for Snodgrass and Vanderwart's (1980) images, as justified by the likelihood tests. Our fully fitted models included random intercepts for participants, items, target word production frequency, visual complexity, and the interaction between stimulus presentation time, feature type, picture-word hemispheric projection, and pathway (Experiment 2) as fixed effects.[7] We derived *p*-values for all main effects and interactions using the Likelihood Ratio Test by comparing the full model to a reduced model excluding the relevant term (Winter 2013, 2019). Planned comparisons were conducted using the *emmeans* package with Tukey's correction (Lenth et al., 2018). The pooled standard deviation between two groups was used as the standardizer for all reports of Cohen's *d* values. Inspection

[7] Regression equation for accuracy analyses: ModelName <- glmer(accuracy ~ presentation_time_condition * feature_type * hemispheric_projection * pathways + (1|participant) + (1|item) + (1|picture_visual_complexity) + (1|word_target_production_frequency), data=FILE, family = binomial). Regression equation for response times analyses: ModelName <- lmer(rt_log ~ presentation_time_condition * feature_type * hemispheric_projection * pathways+ (1|participant) + (1|item) + (1|picture_visual_complexity) + (1|word_target_production_frequency), data=FILE).

of residual plots showed deviations from homoscedasticity and normality for response times. As such, those analyses relied on log-transformed data (Winter, 2013, 2019; Osborne, 2002, but see Lo & Andrews, 2015). All figures were created using the *ggplot2* package (Wickham, 2016).

Additionally, for both experiments, we also conducted two sets of exploratory multiple regression analyses. In the first set, we estimated the effect of feature cue validity and feature distinctiveness values on participants' accuracy on congruency decisions, for high- and low-prototypical features. In the second set, we regressed participants' general accuracy on congruency decisions as a function of feature cue validity and feature distinctiveness values, for living and non-living categories. Results from these analyses, for both experiments, can be found in Appendix D.

## Results and Discussion

Prior to conducting analyses, participants' overall accuracy to congruency decisions was screened. All participants scored above chance (i.e., above 50%) and were thus kept for all analyses. Further, response latencies below 200 ms and greater than 2500 ms (0.71 % of responses) were removed because they were considered either anticipations or they were deemed too long to reflect perceptual processes (see VanRullen & Thorpe, 2001b). Subsequently, participants' responses that were 2.5 standard deviations above or below their respective means (2.82 % of responses) were replaced by their upper or lower standard deviation cut-off values (see Osborne & Overbay, 2004).

### Congruency Decision Accuracy

The full model was compared to a null model consisting of only random predictors and was found to provide a statistically significant better fit to the data, $\chi^2(15) = 773.32$, $p < 0.001$. There were also significant main effects of stimulus presentation time, feature type, and hemispheric projection, as well as all two-way and three-way interactions (see Table 3). As predicted, participants were more accurate when stimuli were presented for 190/200 ms rather than 50/60 ms ($p < 0.001$, $d = 0.54$). Further, participants were more accurate when pictures were projected to the right hemisphere and words were projected to the left hemisphere, as opposed to when pictures and words were projected to the left and right hemispheres, respectively ($p < 0.001$, $d = 0.49$)—supporting the hypothesis of a processing advantage for words projected in the VWFA, in the LH.

**Table 3**

*Logistic regression of accuracy to congruency decisions as a function of feature type and hemispheric projection at the two presentation time points.*

| | Accuracy | | | | |
|---|---|---|---|---|---|
| **Predictor** | **β** | **SE β** | **z-value** | **95% CI of β** | **Null Comparison** |
| Constant | -0.56 | 0.54 | -1.04 | [2.46, 4.61] | |
| Presentation Time | 1.03 | 0.36 | 2.85 | [2.81, 4.88] | $\chi^2(1) = 502.99$, $p < 0.001$ |
| Feature Type | -0.24 | 0.19 | -1.24 | [0.55, 0.99] | $\chi^2(3) = 28.46$, $p < 0.001$ |
| Hemispheric Projection | 0.50 | 0.35 | 1.43 | [1.63, 2.64] | $\chi^2(1) = 204.22$, $p < 0.001$ |
| Presentation Time x Feature Type | 0.14 | 0.13 | 1.08 | [0.58, 1.19] | $\chi^2(3) = 13.27$, $p = 0.004$ |
| Presentation Time x Hemispheric Projection | -0.03 | 0.24 | -0.11 | [0.47, 1.11] | $\chi^2(1) = 11.63$, $p = 0.001$ |
| Feature Type x Hemispheric Projection | 0.21 | 0.13 | 1.65 | [0.79, 1.51] | $\chi^2(3) = 14.08$, $p = 0.003$ |
| Presentation Time x Feature Type x Hemispheric Projection | -0.11 | 0.09 | -1.24 | [0.60, 1.76] | $\chi^2(10) = 43.57$, $p < 0.001$ |

Surprisingly, planned comparisons revealed that in the 50/60 ms presentation time condition, participants were more accurate when they were presented with superordinate features, in comparison to high-prototypical ($p = 0.05$, $d = 0.42$) and low-prototypical features ($p < 0.001$, $d = 0.44$). Further, still in the 50/60 ms presentation time condition, while participants' responses were more accurate for basic level labels than for low-prototypical features ($p = 0.007$, $d = 0.42$), there were no differences in accuracy between basic level labels and high-prototypical features ($p = 0.33$, $d = 0.71$), as well as between basic level labels and superordinate features ($p = 0.44$, $d = 0.18$). Thus, it seems that pairing pictures of objects (e.g., a dog) with a label representing superordinate category information about that object (e.g., ANIMAL) yields greater accuracy than pictures that are paired with labels representing the object's features (e.g., BARK, FUR). This suggests that category information may be accessed prior to the identification of the token object or its properties. We return to this issue in the general discussion.

We found slightly different results in the 190/200 ms presentation time condition. While superordinate features still yielded greater accuracy than high-prototypical ($p < 0.001$, $d = 0.32$) and low-prototypical features ($p < 0.001$, $d = 0.35$), basic level labels now also yielded greater accuracy than high-prototypical ($p = 0.005$, $d = 0.30$) and low-prototypical features ($p < 0.001$, $d = 0.33$). Nevertheless, there were still no differences in accuracy between superordinate features and basic level labels ($p = 1.00$, $d = 0.26$). See Figure 3a for participants' accuracy to congruency decisions when pictures are projected to the left hemisphere and for words projected to the right hemisphere, and Figure 3b for when pictures are projected to the right hemisphere and for words projected to the left hemisphere.

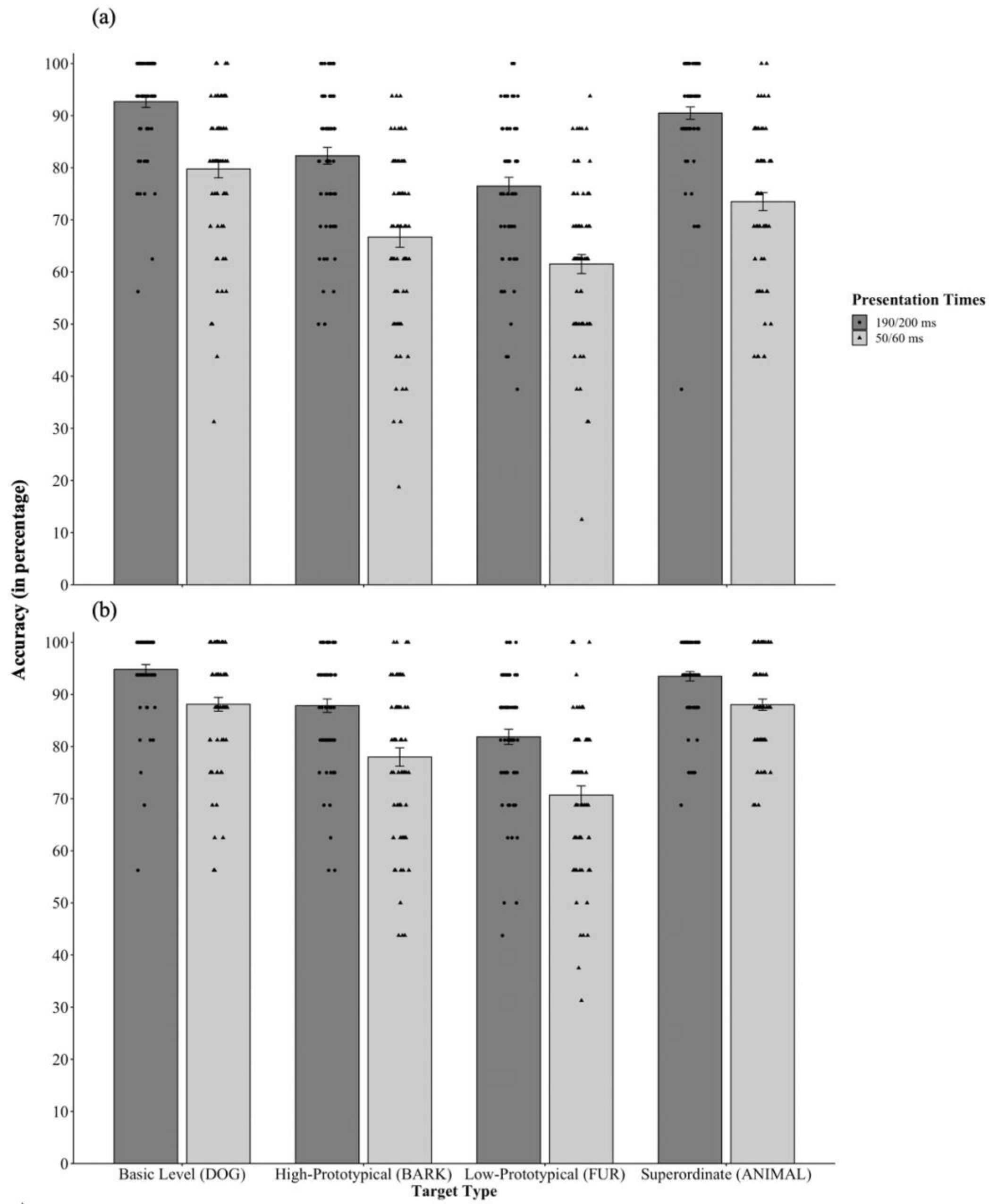


*Figure 3*. Participants' mean accuracy to congruency decisions (a) for pictures projected to the left hemisphere and for words projected to the right hemisphere, and (b) for pictures projected to the right hemisphere and for words projected to the left hemisphere. The x-axis represents the four target type labels (with examples corresponding to the dog picture), and the y-axis represents accuracy in percentage. Error bars represent one standard error of the mean.

Overall, participants' responses were more accurate (1) when images were paired with superordinate features, in the 50/60 ms presentation time condition, (2) when images were paired with superordinate or basic level labels, in the 190/200 ms presentation time condition, (3) when stimuli were presented for 190/200 ms rather than 50/60 ms, and (4) when images and words were projected to the right and left hemispheres, respectively. Crucially, these results suggest that the time-course of conceptual tokening seems to rely on an early access to category information at the superordinate level, which may then be followed by basic level information and features of concepts.

**Response Times**

Only correct responses to the congruency decisions were included in the model. The full model was compared to a null model consisting of only random predictors and was found to provide a statistically significant better fit to the data, $\chi^2(17) = 877.47$, $p < 0.001$. There were also significant main effects of stimulus presentation time, feature type, and hemispheric projection, in addition to a presentation time by feature type interaction. Furthermore, while there was a marginally significant three-way interaction, there was no presentation time by hemispheric interaction, nor was there a feature type by hemispheric projection interaction (see Table 4). We also found that participants' responses were significantly faster when stimuli were presented for 190/200 ms, rather than 50/60 ms ($p = 0.03$, $d = 0.10$). Additionally, participants were faster when pictures and words were projected to the right and left hemisphere, respectively ($p < 0.001$, $d = 0.12$). These results replicate those obtained in the analyses of participants' congruency accuracy.

**Table 4**

*Planned comparisons of the linear regression of response times to congruency decisions as a function of feature type and presentation time points.*

| | Response Times | | | | |
|---|---|---|---|---|---|
| **Predictor** | **β** | **SE β** | **t-value** | **95% CI of β** | **Null Comparison** |
| Constant | 873.79 (2.92) | 63.51 (3.09) | 13.76 | [749.30, 998.27] | |
| Presentation Time | -6.90 (4.32) | 37.93 (1.83) | -0.18 | [-81.23, 67.44] | $\chi^2(1) = 5.40$, $p = 0.02$ |
| Feature Type | -2.43 (6.56) | 22.53 (1.09) | -0.11 | [-46.58, 41.73] | $\chi^2(3) = 84.64$, $p < 0.001$ |
| Hemispheric Projection | -14.05 (-4.65) | 23.79 (1.15) | -0.59 | [-60.67, 32.57] | $\chi^2(1) = 125.4$, $p < 0.001$ |
| Presentation Time x Feature Type | 0.48 (-1.45) | 13.90 (6.72) | 0.03 | [-26.77, 27.72] | $\chi^2(3) = 12.79$, $p = 0.005$ |
| Presentation Time x Hemispheric Projection | -8.51 (-6.81) | 14.76 (7.14) | -0.58 | [-37.43, 20.42] | $\chi^2(1) = 0.26$, $p = 0.61$ |
| Feature Type x Hemispheric Projection | -5.97 (-3.89) | 8.72 (4.21) | -0.69 | [-23.05, 11.11] | $\chi^2(3) = 2.55$, $p = 0.47$ |
| Presentation Time x Feature Type x Hemispheric Projection | 2.86 (2.07) | 5.40 (2.61) | 0.53 | [-7.73, 13.45] | $\chi^2(10) = 17.63$, $p = 0.06$ |

*Note*. Parentheses represent linear regression values in log transformation.

The results of planned comparisons, however, were slightly different than those of participants' accuracy. Namely, at both presentation times—rather than only in the 190/200 ms presentation time condition—participants were significantly faster when pictures were paired with basic level labels and superordinate features, in comparison to high- and low-prototypical features (see Table 5). Similar to accuracy results, there were no differences in RTs between basic level labels and superordinate features across the two presentation times (see Figure 4).

**Table 5**

*Linear regression of response times to congruency decisions as a function of feature type and hemispheric projection at the two presentation time points.*

| Predictor | β | t-value | *p*-value | Cohen's *d* | 95% CI of β |
|---|---|---|---|---|---|
| | | **Presentation Time 1 (50/60 ms)** | | | |
| Basic Level x High-Prototypical | -37.04 (-0.02) | -4.39 | $p = 0.003$ | -0.26 | [-62.61, -11.46] |
| Basic Level x Low-Prototypical | -57.30 (-0.03) | -5.73 | $p < 0.001$ | -0.29 | [-87.60, -26.99] |
| Basic Level x Superordinate | 13.12 (0.01) | 1.75 | $p = 0.65$ | 0.04 | [-9.55, -35.78] |
| Superordinate x High-Prototypical | -50.15 (-0.03) | -6.88 | $p < 0.001$ | -0.29 | [28.04, 72.27] |
| Superordinate x Low-Prototypical | -70.41 (-0.04) | -7.61 | $p < 0.001$ | -0.33 | [42.37, 98.45] |
| High-Prototypical x Low-Prototypical | -20.26 (-0.01) | -2.24 | $p = 0.33$ | -0.03 | [-47.68, 7.17] |
| | | **Presentation Time 2 (190/200 ms)** | | | |
| Basic Level x High-Prototypical | -34.42 (-0.02) | -4.26 | $p < 0.001$ | -0.25 | [-58.88, -9.95] |
| Basic Level x Low-Prototypical | -81.95 (-0.04) | -8.50 | $p < 0.001$ | -0.41 | [-111.19, -52.71] |
| Basic Level x Superordinate | 4.39 (0.001) | 0.62 | $p = 1.00$ | 0.03 | [-25.96, 17.17] |
| Superordinate x High-Prototypical | -47.54 (-0.02) | -5.51 | $p < 0.001$ | -0.22 | [9.28, 50.77] |
| Superordinate x Low-Prototypical | -77.56 (-0.04) | -8.77 | $p < 0.001$ | -0.37 | [50.76, 104, 36] |
| High-Prototypical x Low-Prototypical | -47.54 (-0.02) | -5.51 | $p < 0.001$ | -0.17 | [-73.67, -21.40] |

*Note*. Parentheses represent linear regression values in log transformation.

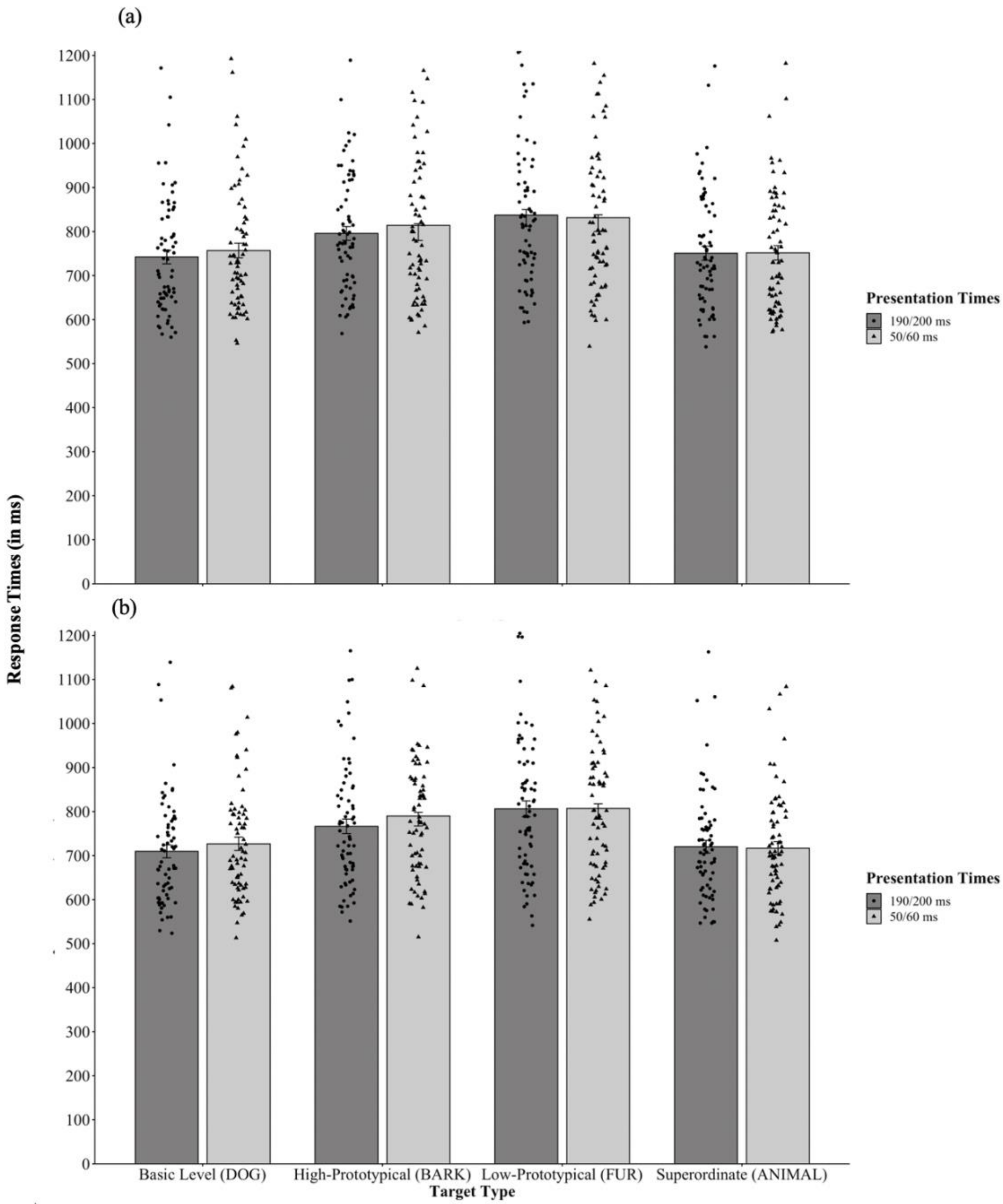


*Figure 4*. Participants' mean response times to congruency decisions (a) for pictures projected to the left hemisphere and for words projected to the right hemisphere, and (b) for pictures projected to the right hemisphere and for words projected to the left hemisphere.

Overall, participants' congruency decisions were faster (1) when images were paired with basic level or superordinate labels, across both presentation times, (2) when stimuli were presented for 190/200 ms instead of 50/60 ms, and (3) when images and words were projected to the right and left hemispheres, respectively.

While these results are overall very similar to those obtained in the analyses of participants accuracy, there was one important difference. Namely, in the 50/60 ms presentation time condition, although participants responded faster to basic level labels than high-prototypical features, there were no differences in accuracy between these two target types. Differences in accuracy between basic level labels and high-prototypical features were only observed in the 190/200 ms presentation time condition. At first glance, these results could be taken to support the idea that, at the earliest moments of concept tokening, high-prototypical features provide an equally good entry level as basic level labels. However, there are two observations that prevent us from fully endorsing this view. First, our results do not show prototypicality effects (i.e., shortest RTs and greatest accuracy for high-prototypical features) at either presentation timepoints. If object concepts are represented through constituent features, we would have expected results to reflect prototypicality effects in the 50/60 ms—the timepoint of concept tokening. Second—and perhaps more importantly—participants' were significantly more accurate when pictures were paired with superordinate features, at both presentation timepoints. Thus, taken together, the results obtained from participants' accuracy and RTs seem to suggest that, at the earliest moments of object concept tokening, what might be accessed is information pertaining to their superordinate categories or information akin to their most generic lexical labels.

It is important to mention that, although the position of each stimulus was carefully controlled to correspond to approximately 3° of visual arc, their actual presentation position could have been affected by the variation in participants' monitor sizes. Consequently, presenting stimuli in positions that are slightly askew could have led to overlapping retinal projections. As such, Experiment 2 was conceived as a follow-up to Experiment 1 in order to control for the potential overlapping retinal projections with the use of anaglyph glasses.

**Experiment 2: Picture-Word Masked Priming Congruency Task with Anaglyphs**

Whereas Experiment 1 investigated the *what* and *when* questions—namely, the time-course and relative contribution of object labels and features to concept tokening—the main goal of Experiment 2 was to further investigate these processes while controlling the potential overlapping retinal projections during the early stages of processing—in case there is no complete foveal split.[8] In particular, Experiment 2 controlled for hemispheric projections by employing a novel, purely psychophysical manipulation using anaglyph glasses. Specifically, the use of anaglyphs allowed us to take advantage of binocular rivalry to investigate the potential differences between hemispheric representations of word labels and objects. A secondary goal of Experiment 2 was to further investigate the potential differences in hemispheric representations across ipsilateral and contralateral visual pathways, during the early stages of word and object processing.

While several studies have focused on the role of hemispheric representations during word and object recognition, less is known about the role of visual pathways during recognition. A study using functional magnetic resonance imagining found an asymmetry in the density of retinal ganglion cells across the two visual pathways (Toosy et al., 2001), whereby contralateral visual pathways contained a larger cell density than ipsilateral visual pathways—an asymmetry also found in macaque monkeys (Perry & Cowey, 1985). As a result, one might expect this anatomical asymmetry to be reflected functionally as a processing advantage for information

[8] Although the foveal split theory is by no means consensus (see Ellis & Brysbaert, 2010a, for a recent discussion on the debate between the split fovea theory and bilateral projection theory), several studies investigating visual word recognition have been taken to support this proposal (Ellis & Brysbaert, 2010b; Shillcock, Ellison, & Monaghan, 2000; Brysbaert, Cai, & Van der Haegan, 2012; Lavidor & Walsh, 2003, 2004; Martin, Thierry, Démonet, Roberts, & Nazir, 2007).

projected through contralateral visual pathways. However, psychophysical studies have yielded mixed results. For instance, in a study conducted by Obregón and Shillcock (2012), the authors found that, when using a haploscope in a perceptual recognition task, four-letter words or letter sequences presented through contralateral visual pathways engendered greater accuracy than those presented via ipsilateral visual pathways. However, in another study, de Almeida, Dumassais, and Antal (2020) investigated the recognition of compounds (e.g., *football*), pseudo-compounds (e.g., *carpet*), and other monomorphemic words (e.g., *elephant*), while manipulating visual pathways with the use of anaglyphs, and found that compounds presented through ipsilateral, rather than contralateral, pathways engendered greater accuracy in a lexical decision task. One possible interpretation for the conflicting results may be in the nature of the stimuli and tasks employed by both studies.

Taken together, although the main goal of Experiment 2 was to replicate Experiment 1 while employing a method that controlled for the potential overlap between retinal projections during early stages of processing, the use of anaglyphs also allowed us to take advantage of binocular rivalry to investigate the differences between hemispheric representations of word labels and objects, via ipsilateral and contralateral visual pathways, and their anatomical projections into the occipito-temporal lobes. That is, by using anaglyphs, the presentation of objects and feature-related words were separated into ipsilateral and contralateral visual hemifields and visual pathways. As such, in addition to the questions explored in Experiment 1, the manipulation of colour combinations (presenting pictures and words in either blue or red, and either in the RVF or LFV) in Experiment 2 allowed us to simultaneously investigate the relative contribution of visual hemifields and visual pathways on the time-course of object concept tokening and feature processing.

## Method

### Participants

The same sample of 71 participants recruited for Experiment 1 participated in Experiment 2.

### Materials, Design, and Procedure

Experiment 2 employed the same 128 picture-word pairs as those employed in Experiment 1. Participants completed the PWPC task outlined in Experiment 1, while wearing red-blue anaglyph glasses (Retsing Eyewear Co., Hangzhou, China), with picture-word pairs presented in red and blue (see Figure 5). The Snodgrass and Vanderwart's (1980) pictures were modified using Photoshop (Adobe, 2019, version 21.0.2) to match the hue that corresponds to the anaglyph glasses (red: RGB 1-0-0; blue: RGB: 0-0-1). This was tested by the experimenters in three computers, under different brightness and resolution conditions. Pictures were cropped such that the size of the image corresponded to the same width of the word stimuli.

Experiment 2 consisted of a 2 x 2 x 2 x 4 factorial design yielding 32 distinct conditions. In addition to the factors manipulated in Experiment 1 (stimulus presentation times, picture-word hemispheric projection, and target type), a new factor, *pathway* (2 levels: ipsilateral, contralateral), was introduced. There was a total of 128 experimental picture-word pairs for each of the 32 conditions, for a total of 4096 token items. The 4096 items were counterbalanced among 32 lists, such that each list contained 4 items from each of the 32 conditions. The list combinations were counterbalanced, such that no participant viewed the same picture-word combination twice. Participants were instructed to wear the anaglyph glasses before the beginning of the experiment, after having completed the set of questionnaires. Similar to Experiment 1, they were instructed to take breaks when needed, by delaying the start of the following trial. Participants completed two lists, in random order, in a given testing session. Without breaks, each list lasted approximately 15 minutes. See Figure 6 for the time-course of events in a sample trial.

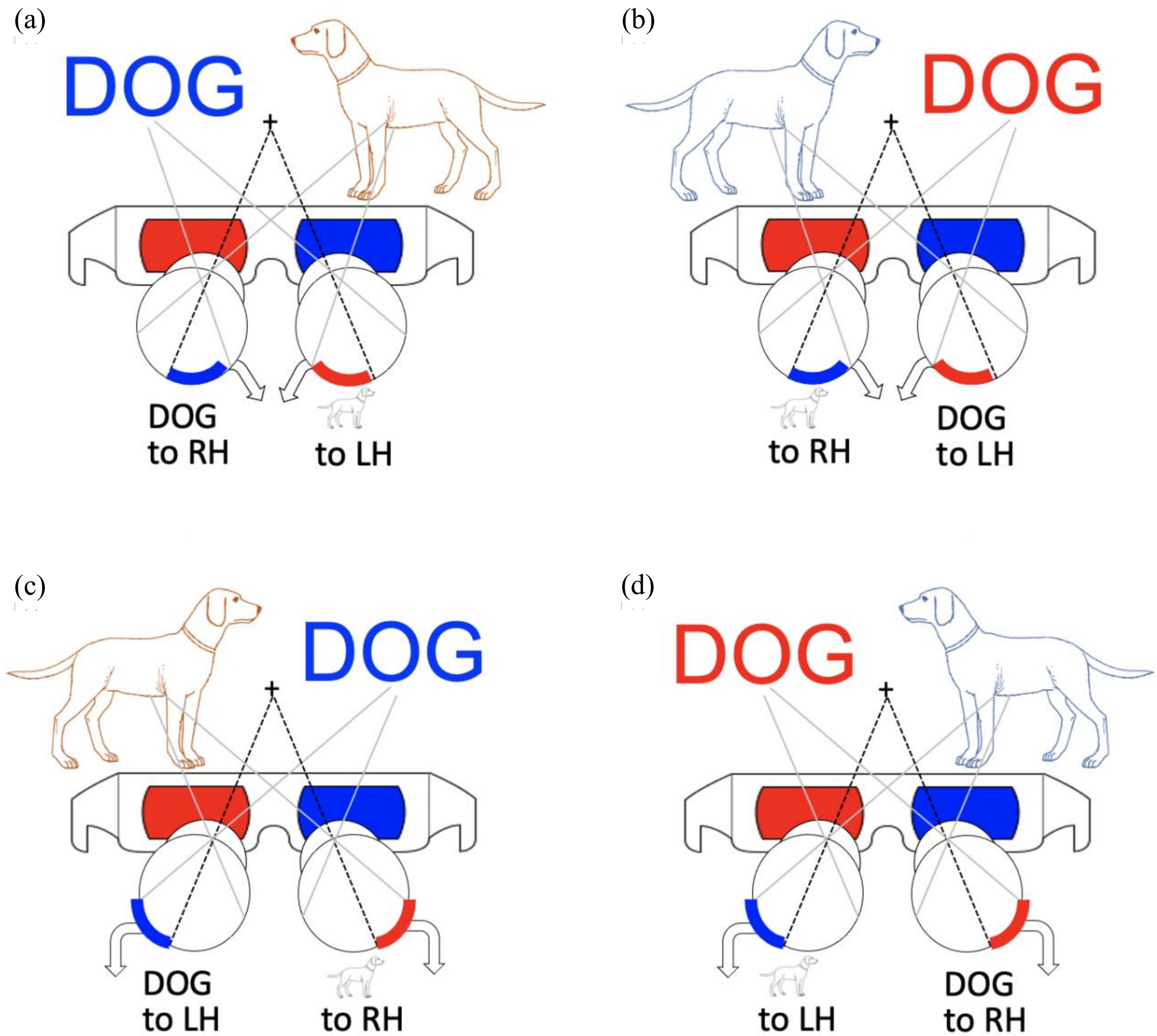


*Figure 5*. Example of stimuli with the information being projected in the two hemispheres through the contralateral (a, b) and ipsilateral (c, d) visual pathways, as indicated by the arrows. The patch of red or blue in the schematic retina represents the stimulus color that was processed by each eye at the portion of the retina relative to the fovea, whose location is represented by the dotted line and corresponds to the fixation cross (+). RH: Right Hemisphere; LH: Left Hemisphere.

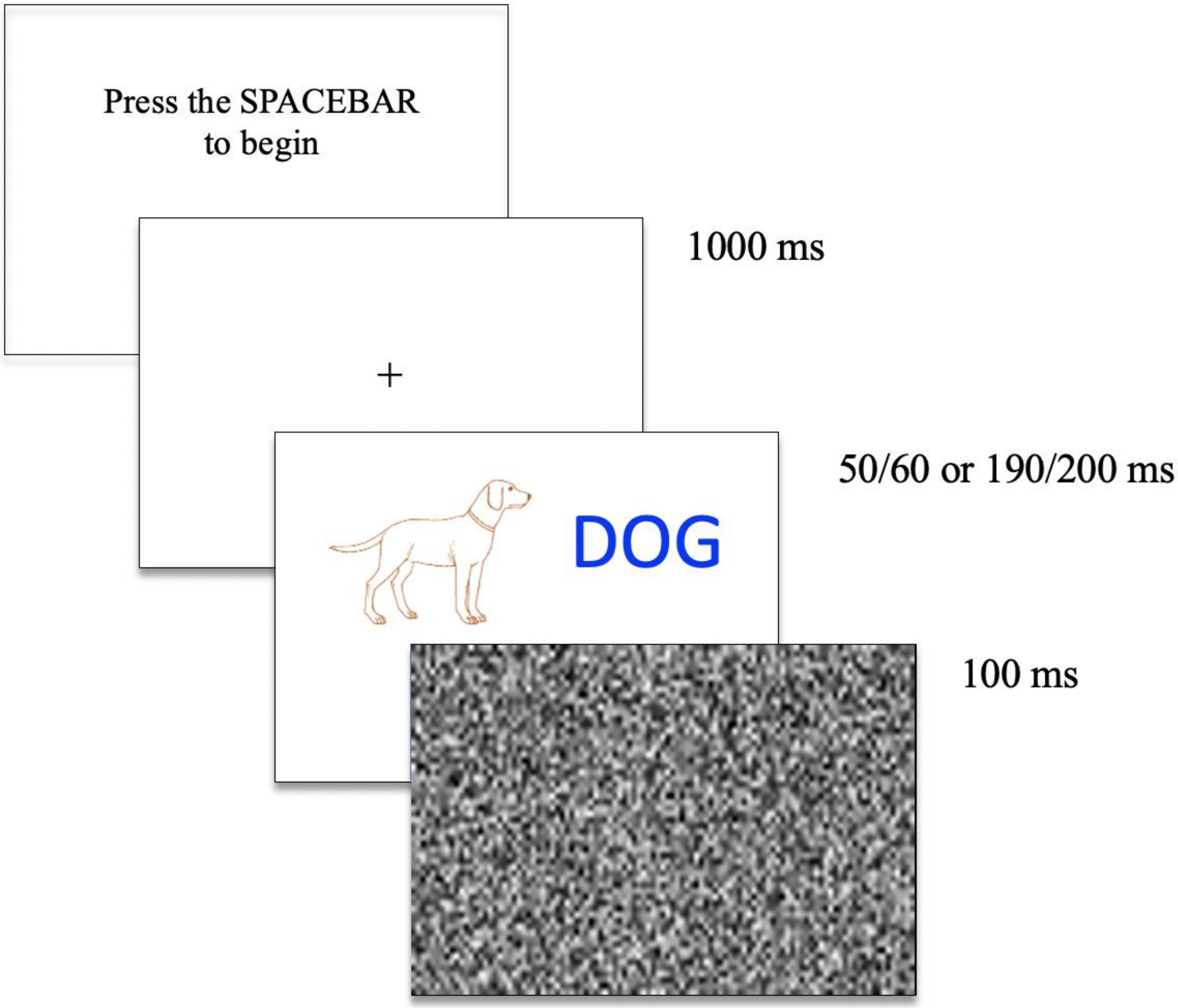


*Figure 6*. Time-course of events in each trial, in Experiment 2, with participants wearing anaglyph glasses.

## Results and Discussion

Prior to conducting analyses, participants' overall accuracy to the congruency decision was screened. One participant scored below chance (i.e., below 50%) and was thus removed from all analyses. Similarly to Experiment 1, RTs below 200 ms and greater than 2500 ms (0.01 % of responses) were removed. Subsequently, participants' responses that were 2.5 standard deviations above or below their respective means (3.19 % of responses) were replaced by their upper or lower standard deviation cut-off values.

### Congruency Decision Accuracy

The full model was compared to a null model consisting of only random predictors and was found to provide a statistically significant better fit to the data, $\chi^2(31) = 1173.30$, $p < 0.001$. There were also significant main effects of stimulus presentation time, feature type, hemispheric projection, and pathway, as well as several two-, three- and four-way interactions (see Table 6 for results from all main effect and interaction analyses). Furthermore, as found in Experiment 1, participants' responses were more accurate (a) when picture-word pairs were presented for 190/200 ms rather than 50/60 ms ($p < 0.001$, $d = 0.62$), and (b) when pictures were projected to the right hemisphere and words were projected to the left hemisphere, as opposed to when pictures and words were projected to the left and right hemispheres, respectively ($p < 0.001$, $d = 0.51$). Similarly to de Almeida, Dumassais, and Antal (2020), but contrary to Obregón and Schillcock (2020), participants were more accurate when picture-word pairs were projected through ipsilateral visual pathways, instead of contralateral visual pathways ($p < 0.001$, $d = 0.41$).

**Table 6**

*Logistic regression of accuracy to congruency decisions as a function of feature type, hemispheric projection, and pathway, at the two presentation time points.*

| | | | Accuracy | | |
|---|---|---|---|---|---|
| **Predictor** | **β** | **SE β** | **z-value** | **95% CI of β** | **Null Comparison** |
| Constant | 2.32 | 1.55 | 1.49 | [0.48, 10.19] | |
| Presentation Time | -0.48 | 1.08 | -0.44 | [0.08, 0.62] | $\chi^2(1) = 826.68$, $p < 0.001$ |
| Feature Type | -1.14 | 0.56 | -2.03 | [0.11, 0.32] | $\chi^2(3) = 25.68$, $p < 0.001$ |
| Hemispheric Projection | -1.60 | 1.02 | -1.57 | [0.03, 0.20] | $\chi^2(1) = 232.74$, $p < 0.001$ |
| Pathway | -2.61 | 0.99 | -2.64 | [0.01, 0.07] | $\chi^2(1) = 10.13$, $p = 0.002$ |
| Presentation Time x Feature Type | 0.41 | 0.39 | 1.06 | [0.71, 1.51] | $\chi^2(3) = 39.18$, $p < 0.001$ |
| Presentation Time x Hemispheric Projection | 0.84 | 0.72 | 1.17 | [0.57, 1.32] | $\chi^2(1) = 0.14$, $p = 0.71$ |
| Presentation Time x Pathway | 1.25 | 0.69 | 1.80 | [0.89, 1.47] | $\chi^2(1) = 2.95$, $p = 0.085$ |
| Feature Type x Hemispheric Projection | 0.72 | 0.37 | 1.94 | [0.99, 1.06] | $\chi^2(3) = 7.12$, $p = 0.068$ |
| Feature Type x Pathway | 0.87 | 0.36 | 2.42 | [1.18, 1.38] | $\chi^2(3) = 2.44$, $p = 0.49$ |
| Hemispheric Projection x Pathway | 1.36 | 0.66 | 2.08 | [1.08, 1.88] | $\chi^2(1) = 0.03$, $p = 0.87$ |
| Presentation Time x Feature Type x Hemispheric Projection | -0.22 | 0.26 | -0.87 | [0.48, 0.80] | $\chi^2(10) = 50.79$, $p < 0.001$ |

| | | | | | |
|---|---|---|---|---|---|
| Presentation Time x Feature Type x Pathway | -0.35 | 0.25 | -1.39 | [0.43, 0.71] | $\chi^2(10) = 50.86$, $p < 0.001$ |
| Presentation Time x Hemispheric Projection x Pathway | -0.51 | 0.46 | -1.10 | [0.24, 0.60] | $\chi^2(4) = 4.32$, $p = 0.37$ |
| Feature Type x Hemispheric Projection x Pathway | -0.44 | 0.24 | -1.87 | [0.40, 0.64] | $\chi^2(10) = 19.67$, $p = 0.03$ |
| Presentation Time x Feature Type x Hemispheric Projection x Pathway | 0.14 | 0.17 | 0.83 | [0.83, 1.15] | $\chi^2(25) = 77.27$, $p < 0.001$ |

One possible interpretation for these conflicting results may be in the nature of the stimuli and techniques employed by our study and that of Obregón and Schillcock (2002). As such, we need to be cautious when directly comparing the results obtained from both studies. We return to this issue in the General Discussion.

Crucially, results from planned comparisons replicated those obtained in Experiment 1. That is, in the 50/60 ms presentation time condition, participants were more accurate when images where paired with superordinate features, in comparison to high-prototypical ($p$ = 0.03, $d$ = 0.46) and low-prototypical features ($p$ = 0.007, $d$ = 0.47). There were still no differences in accuracy between basic level labels and superordinate features ($p$ = 0.44, $d$ = 0.04), nor were there differences between basic level labels and high-prototypical ($p$ = 1.00, $d$ = 0.78) and low-prototypical features ($p$ = 0.64, $d$ = 0.77). Rather, as obtained in Experiment 1, differences between basic level labels and high- and low-prototypical features only occurred in the 190/200 ms presentation time condition (high-prototypical: $p$ = 0.003, $d$ = 0.35; low-prototypical: $p$ < 0.001, $d$ = 0.51; see Figure 7). Thus, it seems that in the early stages of concept tokening, pictures (e.g., dog) that are paired with a superordinate label (e.g., *animal*) lead to more accurate responses than pictures that are paired with a frequent feature (e.g., *bark*; high-prototypical) or a less frequent feature (e.g., *fur*; low-prototypical) associated with that picture. However, as presentation times increase, pictures that are paired with their basic-level labels (e.g., *dog*) yield the same level of accuracy as those that are paired with a superordinate label (e.g., *animal*). Together, these results suggest that the content that is accessed by object concepts might be relative to the timing of their presentation durations. Namely, during the early moments of concept tokening, what might first be accessed is information related to objects at the superordinate level. Then, as presentation time increases, information about object categories at the superordinate and basic levels is tokened—but the early analysis of the stimuli may not rely on the tokening of an objects' high- and low-prototypical features. These issues are further addressed in the General Discussion.

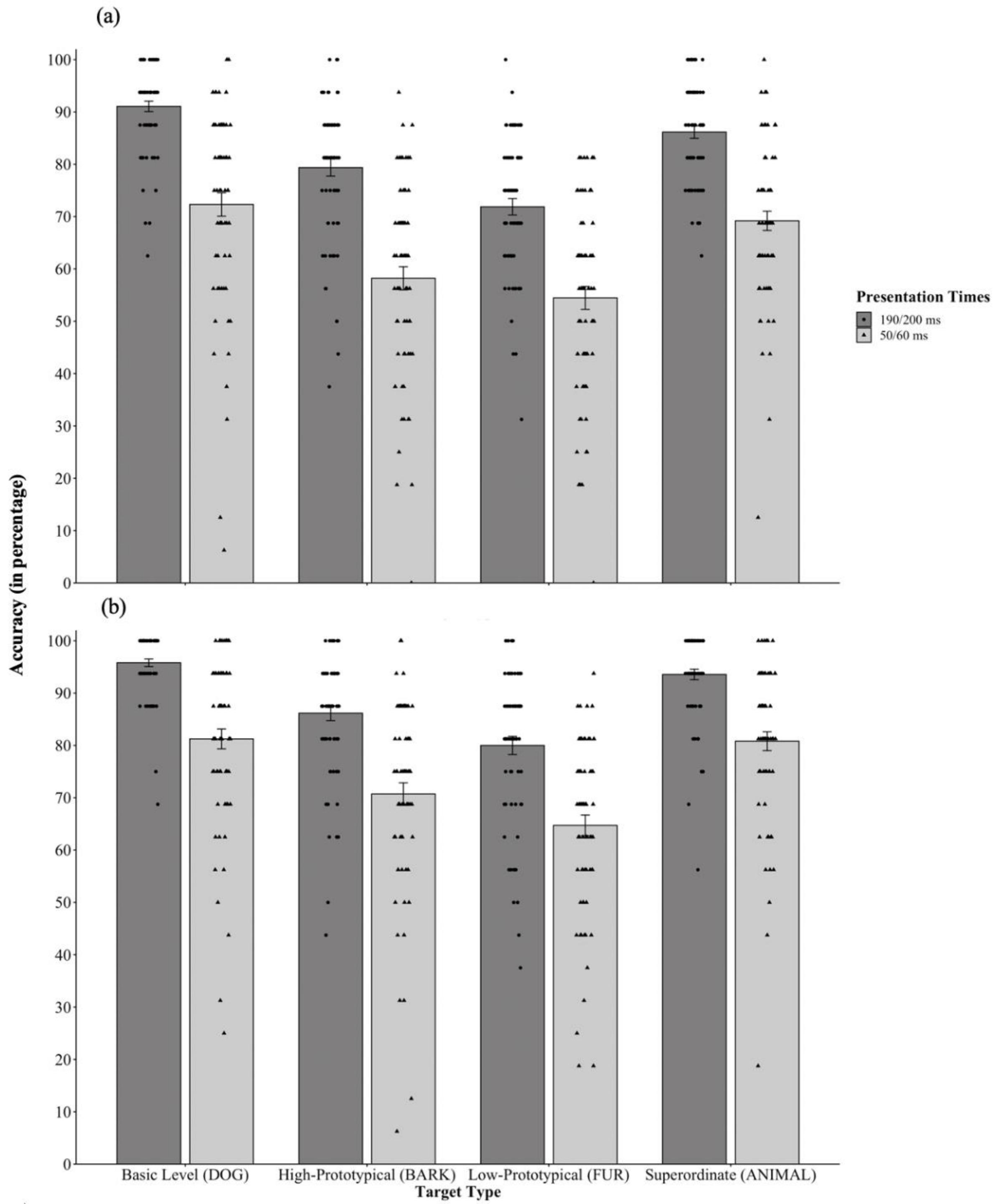


*Figure 7*. Participants' mean accuracy to congruency decisions (a) for pictures projected to the left hemisphere and for words projected to the right hemisphere, and (b) for pictures projected to the right hemisphere and for words projected to the left hemisphere.

**Response Times**

Similar to Experiment 1, only correct congruency decisions were included in the model. The full model was compared to a null model consisting of only random predictors and was found to provide a statistically significant better fit to the data, $\chi^2(31) = 238.99$, $p < 0.001$. There were also significant main effects of stimulus presentation time, feature type, and hemispheric projection, as well as a marginal presentation time by feature type interaction. Further, participants' responses were faster (a) when stimuli were presented for 190/200 ms, rather than 50/60 ms ($p < 0.001$, $d = 0.30$), and (b) when pictures and words were projected to the right and left hemisphere, respectively ($p < 0.001$, $d = 0.17$; see Table 7). It is important to note that these results have been consistently replicated across accuracy and RT analyses, in both experiments.

Results from planned comparisons are also consistent with those of Experiment 1. Specifically, at both presentation times, participants' RTs were significantly faster when pictures were paired with basic level labels and superordinate features, in comparison to high- and low-prototypical features (see Table 8 for results to all planned comparisons). There were also no differences in RTs between basic level labels and superordinate features across the two presentation times (see Figure 8).

**Table 7**

*Logistic regression of response times to congruency decisions as a function of feature type, hemispheric projection, and pathway, at the two presentation time points.*

| | Accuracy | | | | |
|---|---|---|---|---|---|
| **Predictor** | **β** | **SE β** | **t-value** | **95% CI of β** | **Null Comparison** |
| Constant | 826.03 (2.91) | 62.32 (2.95) | 13.26 | [703.88, 948.18] | |
| Presentation Time | 24.03 (5.54) | 36.70 (1.73) | 4.67 | [-47.90, 95.96] | $\chi^2(1) = 21.49, p < 0.001$ |
| Feature Type | 7.98 (8.54) | 22.10 (1.04) | 3.36 | [-35.33, 51.30] | $\chi^2(3) = 54.48, p < 0.001$ |
| Hemispheric Projection | 30.51 (8.03) | 37.25 (1.75) | 3.82 | [-42.51, 103.52] | $\chi^2(1) = 135.16, p < 0.001$ |
| Pathway | 133.23 (6.56) | 84.87 (4.00) | 1.57 | [-33.11, 299.58] | $\chi^2(1) = 0.05, p = 0.82$ |
| Presentation Time x Feature Type | -5.41 (-1.61) | 13.51 (1.08) | -0.40 | [-31.89, 21.07] | $\chi^2(3) = 6.55, p = 0.087$ |
| Presentation Time x Hemispheric Projection | -33.36 (-1.15) | 22.90 (1.08) | -1.46 | [-78.25, 11.52] | $\chi^2(1) = 0.96, p = 0.33$ |
| Presentation Time x Pathway | -81.83 (-5.23) | 51.87 (6.43) | -1.58 | [-183.50, 19.84] | $\chi^2(1) = 0.24, p = 0.63$ |
| Feature Type x Hemispheric Projection | -14.10 (-3.79) | 13.66 (2.44) | -1.03 | [-40.88, 12.67] | $\chi^2(3) = 4.45, p = 0.22$ |
| Feature Type x Pathway | -29.12 (-1.59) | 31.00 (1.46) | -0.94 | [-89.89, 31.64] | $\chi^2(3) = 3.22, p = 0.36$ |
| Hemispheric Projection x Pathway | -78.61 (-3.76) | 52.65 (2.48) | -1.49 | [-181.81, 24.58] | $\chi^2(1) = 1.21, p = 0.27$ |

| | | | | | |
|---|---|---|---|---|---|
| Presentation Time x Feature Type x Hemispheric Projection | 5.92 (1.52) | 8.40 (3.95) | 0.71 | [-10.54, 22.37] | $\chi^2(10) = 12.56$, $p = 0.25$ |
| Presentation Time x Feature Type x Pathway | 19.53 (1.01) | 18.98 (8.94) | 1.03 | [-17.66, 56.73] | $\chi^2(10) = 12.73$, $p = 0.24$ |
| Presentation Time x Hemispheric Projection x Pathway | 44.71 (1.95) | 32.29 (1.52) | 1.39 | [-18.58, 107.99] | $\chi^2(4) = 4.28$, $p = 0.37$ |
| Feature Type x Hemispheric Projection x Pathway | 15.15 (7.85) | 19.22 (9.05) | 0.79 | [-22.51, 52.82] | $\chi^2(10) = 11.38$, $p = 0.33$ |
| Presentation Time x Feature Type x Hemispheric Projection x Pathway | -8.71 (-4.15) | 19.22 (5.56) | 0.74 | [-31.84, 14.42] | $\chi^2(25) = 27.29$, $p = 0.34$ |

*Note*. Parentheses represent linear regression values in log transformation.

**Table 8**

*Linear regression of response times to congruency decisions as a function of feature type and hemispheric projection at the two presentation time points.*

| Predictor | β | t-value | *p*-value | Cohen's *d* | 95% CI of β |
|---|---|---|---|---|---|
| **Presentation Time 1 (50/60 ms)** | | | | | |
| Basic Level x High-Prototypical | -34.60 (-1.52) | -3.69 | $p = 0.006$ | -0.26 | [-63.06, -6.14] |
| Basic Level x Low-Prototypical | -49.19 (-2.21) | -4.43 | $p < 0.003$ | -0.32 | [-82.87, -15.52] |
| Basic Level x Superordinate | 14.43 (0.73) | 1.74 | $p = 0.66$ | 0.06 | [-10.67, 39.52] |
| Superordinate x High-Prototypical | -49.03 (-2.49) | -6.03 | $p < 0.001$ | -0.32 | [24.38, 73.67] |
| Superordinate x Low-Prototypical | -63.62 (-3.12) | -6.19 | $p < 0.001$ | -0.38 | [32.45, 94.79] |
| High-Prototypical x Low-Prototypical | -14.59 (-2.95) | -1.44 | $p = 0.84$ | -0.05 | [-45.27, 16.08] |
| **Presentation Time 2 (190/200 ms)** | | | | | |
| Basic Level x High-Prototypical | -39.24 (-1.82) | -4.49 | $p < 0.001$ | -0.28 | [-65.74, -12.75] |
| Basic Level x Low-Prototypical | -64.70 (-3.12) | -6.12 | $p < 0.001$ | -0.38 | [-96.76, -32.65] |
| Basic Level x Superordinate | 4.49 (0.53) | 0.59 | $p = 1.00$ | 0.02 | [-27.72, 18.73] |
| Superordinate x High-Prototypical | -34.75 (-1.82) | -4.69 | $p < 0.001$ | -0.25 | [12.27, 57.23] |
| Superordinate x Low-Prototypical | -60.21 (-3.12) | -6.19 | $p < 0.001$ | -0.36 | [30.74, 89.68] |
| High-Prototypical x Low-Prototypical | -25.46 (-1.30) | -2.68 | $p = 0.13$ | -0.10 | [-54.22, 3.30] |

*Note*. Parentheses represent linear regression values in log transformation.

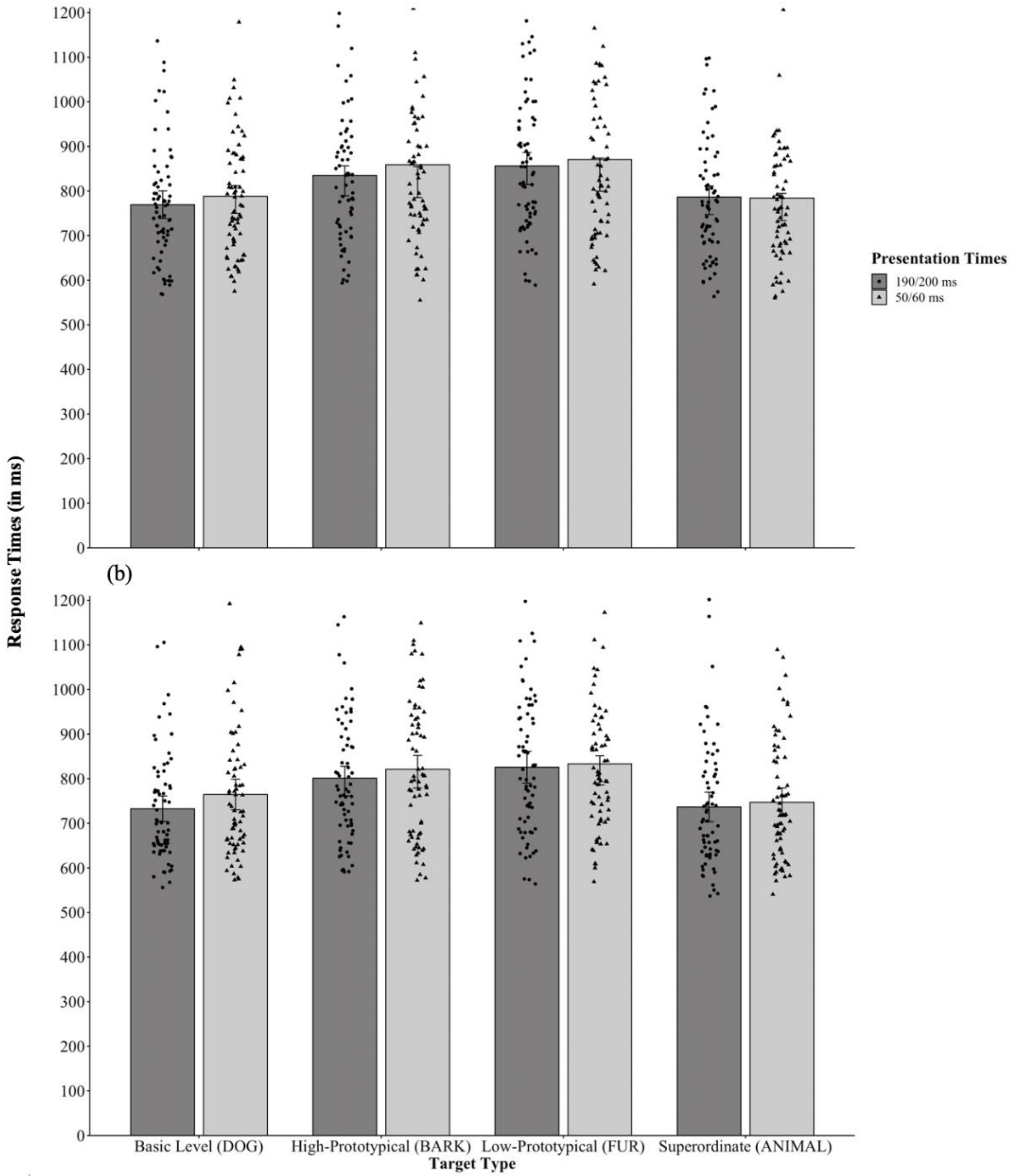


*Figure 8*. Participants' mean response times to congruency decisions (a) for pictures projected to the left hemisphere and for words projected to the right hemisphere, and (b) for pictures projected to the right hemisphere and for words projected to the left hemisphere.

Altogether, results are a replication of those obtained in Experiment 1: participants' RTs were faster (a) when pictures were paired with superordinate features or basic level labels, across both presentation times, (b) when picture-word pairs were presented for 190/200 ms, and (c) when pictures and words were projected to the right and left hemispheres, respectively. Moreover, regarding visual pathways, responses were faster when picture-word pairs were projected through ipsilateral visual pathways. These results suggest that the content which gives access to object concepts may rely on 'whole' objects or lexical labels representing whole objects at the superordinate or basic level, not constituent features.

## General Discussion

The goal of the present study was to investigate the nature of object concepts by probing what kind of information is accessed at the moment of concept tokening. In particular, we sought to investigate two overarching questions: (1) what kind of information is accessed when we token object concepts—do we gain access to object concepts 'holistically', or do we gain access to their constituent properties; and (2) when is that information accessed—that is, what is the time course of conceptual access for objects?

In Experiment 1, we investigated these questions by employing a PWPC task with short presentation duration times (50/60 ms or 190/200 ms), thus probing at relatively "early" and "late" points in the time course of conceptual processing. In Experiment 2, we further investigated the two overarching questions while controlling for potentially overlapping retinal projections during early stages of processing, by employing a novel psychophysical method using anaglyph glasses. This method allowed us to investigate the potential differences in hemispheric representations for word labels and objects, across ipsilateral and visual pathways.

We hypothesized that, if object concepts are represented through sets of constituent features, participants should give more accurate and faster responses when presented with high-prototypical features, regardless of the presentation duration. Conversely, if concepts are represented through 'atomic', non-decompositional primitive representations, participants should give more accurate and faster responses when presented with basic level labels. Further, we hypothesized that high-prototypical features would yield the greatest accuracy and shortest RTs only in the longer presentation duration condition (i.e., 190/200 ms)—given that features should only be accessed after concept tokening.

Regarding congruency decisions, in both Experiment 1 and 2, participants responded with greater accuracy when stimuli were presented for 190/200 ms, rather than 50/60 ms. But more importantly, in the short presentation time condition (i.e., 50/60 ms), pictures presented with superordinate features were judged with greater accuracy than those paired with high- or low-prototypical features. A similar effect was also found in the longer presentation time condition (i.e., 190/190 ms), whereby participants responded with greater accuracy to superordinate and basic level word targets, in comparison to high- and low-prototypical feature targets. It is important to mention that, while accuracy to basic level labels was numerically much greater than that of high-prototypical features in the short presentation time condition (mean difference of approximately 13%)—which is arguably the timepoint of concept tokening—they did not differ from each other statistically. This could be taken to suggest that the content represented by object labels and high-prototypical feature labels are equally good entry levels for concept tokening. However, given that effect size between the two target types was appreciable (Experiment 1: $d = 0.71$; Experiment 2: $d = 0.78$), this may nevertheless suggest that basic level labels engender a slight conceptual access advantage over high-prototypical features. Crucially, given that participants were statistically more accurate when pictures were paired with superordinate features, at both presentation timepoints, this suggests that what might first be accessed during concept tokening is content related to 'whole' objects (e.g., basic shape). The lack of statistical difference in congruency accuracy, and the relatively small effect size measures between superordinate and basic level labels (Experiment 1: $d = 0.18$; Experiment 2: $d = 0.04$) could also be taken to support this idea—especially since both arguably represent 'whole' objects or whole classes of objects rather than a particular property of an object. What seems to be clear from the data is that no prototypicality effects were observed in either presentation time conditions. Moreover, if concepts were represented through sets of features, we should have observed greater accuracy for pictures that were paired with high-prototypical features, regardless of presentation time condition, given that the picture-word pair supposedly points to the same concept (e.g., BARK → DOG). However, the results we obtained do not support this idea. Rather, during the earliest moments of concept tokening, participants' responses are more accurate when pictures are paired with superordinate features. This effect was also found in the longer presentation time condition (i.e., 190/200 ms), with basic level labels also engendering greater accuracy than pictures paired with high- and low-prototypical features.

Regarding decision latencies, results obtained from both experiments also warrant similar interpretations. As predicted, participants RTs were faster when picture-word pairs were presented for 190/200 ms, rather than 50/60 ms. More importantly, across both presentation time conditions, participants RTs were faster when pictures were paired with superordinate or basic level labels, in comparison to high- or low-prototypical features. There were no differences in RTs between superordinate and basic level labels, at both presentation timepoints. It is important to mention, however, that the effect sizes obtained from all RTs analyses are relatively small (range: 0.02-0.48). Thus, although presentation times and target types seem to significantly affect participants RTs to congruency decisions, the magnitude of this effect may be minimal. Moreover, it is also important to mention that causation should ensue when interpreting results stemming from decision latencies, given that the log-transformations changed the metric of the variable (see Osborne, 2002).

Overall, our results seem to suggest that the time-course of concept tokening may first rely on an early access to category information at the superordinate level (e.g., ANIMAL), which is then followed by information related to the objects' basic-level label (DOG) and its features (BARK, FUR, etc.). Moreover, although our study employed a picture-word congruency task—which is arguably more externally and ecologically valid than other paradigms, whereby participants were not primed to lock into pre-determined categories—the superordinate advantage obtained in our study has also been found in other studies employing go/no-go and categorization tasks (Wu, Crouzet, Thorpe, & Fabre-Thorpe, 2014; Poncet & Fabre-Thorpe, 2014; Rogers & Patterson, 2007; Large, Kiss, & McMullen, 2004), and under ultra-rapid categorization conditions (Fabre-Thorpe et al., 2003; Thorpe, Fize, & Marlot, 1996; Macé et al., 2009; VanRullen & Thorpe, 2001a, 2001b).

One possible interpretation for why high- and low-prototypical features did not lead to greater accuracy and shorter RTs than superordinate and basic level labels may be that different feature subcategories (e.g., dimension, part-to-whole, body-part, visual, concept-association—see Table 2) preferentially token particular kinds of concepts. The differences in feature subcategories preferentially triggering different kinds of concepts may also vary across abstract and concrete concepts (e.g., see Wiemer-Hastings & Xu, 2005). In the approach taken here, all objects were concrete and the most important feature was taken to be the high-prototypical one—viz., the one most frequently listed for that object. However, it is possible that DOG is primarily accessed via body-parts, such as TAIL, or PAWS, or through a particular quality, such as LOYAL. Thus, by collapsing all feature subcategories across the four target types (i.e., basic level, superordinate, high-prototypical, and low-prototypical), this may have reduced any advantage brought about the high- and low-prototypical features. An analysis of participants accuracy and RTs by feature type could help clarify whether concept tokening varies as a function of feature kind (e.g., the feature *tail* or *paw* may preferentially token DOG). This would potentially allow us to determine whether the content represented at the superordinate and basic level always gives preferential access to concept tokening, or whether concept tokening varies as a function of feature kinds—whereby some object concepts (e.g., man-made objects, CHAIR) may be preferentially tokened by some feature subcategory (e.g., functional, *for-sitting*).

Another possible interpretation is that pictures paired with superordinate and basic level labels may trigger the same 'holistic' concept (e.g., ANIMAL and DOG → DOG), and thus lead to a priming advantage. Conversely, pictures presented with high- and low-prototypical features may not point to the same concept (e.g., the feature *bark* tokens BARK, not DOG). As a result, when pictures are presented with high- or low-prototypical features, there is a cost in congruency decisions—both in terms of accuracy and RTs—associated with having to generate and inference to determine *how* the feature and picture are related to each other.

It is also possible that the superordinate and basic level labels trigger their own conceptual representations (i.e., *animal* → ANIMAL, and *dog* → DOG), but the time-course of tokening is relative to the quality and availability of the perceptual features that are required for congruency decisions, across the four target types (see Mack & Palmeri, 2011). That is, akin to ultra-rapid categorization paradigms, it is possible that the paradigm we employed—and the brief presentation times—limited the quality and amount of perceptual information required for participants to judge the congruency of categories that may depend on the processing of finer perceptual details. As such, it is plausible that superordinate labels yielded a greater accuracy and RT advantage over other target types because tokening concepts at the superordinate level requires less perceptual processing, and thus gives a faster direct entry to the representation.

However, in the case of basic level labels, high-prototypical, and low-prototypical features, additional exposure time may be required for participants to encode finer perceptual details that might be necessary for congruency decisions—with basic level labels requiring less additional time than features. The idea that more perceptual time would be required may be supported by the fact that, across both experiments, accuracy and RTs to basic-level labels were greater than high-prototypical features, only in the longer presentation time condition. No differences were found in the shorter presentation duration condition.

Taken together, this pattern of results would suggest that the perceptual information available during the early moments of object recognition may preferentially token object representations at the superordinate level, whereby an initial stage of superordinate-level categorization precedes categorization at other levels (e.g., Thorpe et al., 1996). However, we are cautious with this interpretation—in particular because results from both experiments failed to reveal differences in accuracy and RTs between superordinate and basic level labels, in either presentation time conditions. Perhaps, the presentation times employed in the short condition (i.e., 50/60 ms) hovered the timepoint at which perceptual information first began to make contact with object representations at the basic-level—while superordinate representations were already tokened after about 30 ms. This might explain why superordinate features always yielded greater accuracy and RTs over high- and low-prototypical features, whereas basic-level labels only reached that advantage in the longer presentation condition. That said, one important direction for future research would be to employ the present paradigm across multiple presentation times—ranging, e.g., from 30 ms to 5000 ms. Nevertheless, what seems to be clear is that our results do not support the proposal that an initial stage of basic-level categorization precedes categorization at other levels (e.g., Grill-Spector & Kanwisher, 2005).

Regarding hemispheric projections, both experiments yielded the same results: participants' responses were faster and more accurate when picture-word pairs were projected to the right and left hemisphere, respectively. It is important to note that these results were obtained even after controlling for the potential overlap between retinal projections during early stages of processing, in Experiment 2. Altogether, these results suggest that, contra to the bilateral projection theory (Lavidor & Walsh, 2004; Jordan, Paterson, Stachurski, 2008), there may not be an area of substantial overlap around the fovea, whereby information is simultaneously projected to both hemispheres. Rather, the strong LH advantage found for word targets—an effect amply shown in the literature (e.g., Finkbeiner, Almeida & Caramazza, 2006; Bub & Lewine, 1988; Hunter & Brysbaert, 2008)—suggests that there may be a perfect vertical split at the fovea. The accuracy and RT advantage for words and pictures projected to the LH and RH, respectively, might also be due to the words' supposedly direct access to the VWFA—the area specialized for word forms in the LH (Cohen et al., 2000, 2002; Cohen & Dehaene, 2004). Consequently, words projected to the RH may have engendered lower accuracy and longer RTs due to the required inter-hemispheric transfer of information—a transfer that is hypothesized to take minimally 10 ms (Cohen et al., 2000).

Moreover, the use of anaglyph glasses in Experiment 2 also brought about a novel methodological contribution. Namely, combining anaglyphs with dichoptic presentations allowed us to take advantage of binocular rivalry to investigate the relative contribution of visual pathways on the hemispheric representations of objects and word labels. Results showed that participants were significantly more accurate when picture-word pairs were presented through ipsilateral visual pathways. While our results are similar to those obtained by de Almeida and colleagues (2020), they are at odds with those obtained by Obregón and Schillcock (2002).

One interpretation for these conflicting results may be attributed to differences in the tasks employed. While our study employed a congruency judgment task, Obregón and Schillcock (2002) used a perceptual task, instructing participants to ‘name any word or letters they saw’ (p. 3281). Arguably, recalling a sequence of letters—in trials when participants chose to respond in that manner—can be achieved without necessarily tokening a conceptual representation. In our task, however, participants *must* token the representation of both, pictures and words, in order to make their congruency decisions. Moreover, our results may be congruent with those obtained by de Almeida et al. (2020) because the task they employed—namely, a lexical decision task—also relies on the tokening of word representations. As such, it is possible that the results obtained by Obregón and Schillcock (2002) reflect different underlying cognitive processes than those obtained by de Almeida et al. (2020) as well as those obtained in the present study.

Another possible interpretation for the discrepancy between our results and those obtained by Obregón and Schillcock (2002) may be in the nature of the stimuli that both studies employed. For instance, Obregón and Schillcock separated four-letter words into two halves, which consequently always projected two ‘non-words’ to each hemisphere. In our study, however, each hemisphere was always projected a real word of English. This was also the case in the main experimental manipulations of de Almeida et al.’s (2020) study (e.g., legally split compounds: BLUE-BERRY; legally split pseudo-compounds: SHAM-ROCK). Thus, it is possible that during the earliest moments of visual word recognition, the conceptual system is attuned to detect morphemes—rather than letter features (e.g., lines). Consequently, and perhaps more importantly, it may be the case that words (i.e., morphemes) projected through ipsilateral pathways engender greater accuracy because the temporal hemiretina of the left eye directly projects its representations to area V1 in the LH—and its higher projections, including the

VWFA—whereas projections from the contralateral pathways do not directly project their representations to the LH. Rather, projections from contralateral pathways require information to cross-over at the optic chiasm, which may engender a cost. Further, this cost may be exacerbated when word representations are projected to the RH via contralateral pathways, requiring an additional inter-hemispheric transfer at the corpus callosum. Altogether, it seems that the relative contribution of visual pathways on the hemispheric representations of objects and word labels is dependent on the content of the stimuli that is being projected—not on the sheer density of ganglion cells in the contralateral visual pathway.

In summary, we conducted two experiments to investigate the nature of conceptual tokening—whether concepts are accessed via the content of lexical labels representing whole objects or through the content of lexical labels representing their constituent conceptual properties—using a picture-word masked priming congruency task with brief exposures (i.e., 60/60 ms or 190/200 ms). In Experiment 1, participants were presented with picture-word pairs and had to judge whether the stimuli were related to each other. In Experiment 2, we employed a novel psychophysical method using anaglyphs, whereby participants completed the same picture-word masked priming congruency task while wearing anaglyph glasses. The use of anaglyphs allowed us to address functional and neuroanatomical questions, during the earliest moments of conceptual tokening. That is, this manipulation allowed us to control for the potential overlap between retinal projections during early stages of processing. Crucially, combining anaglyphs with dichoptic presentations allowed us to take advantage of binocular rivalry to investigate the hemispheric projection of objects and word labels at different levels of representation (i.e., basic, superordinate, high-prototypical, and low-prototypical). Results from both experiments suggest that, during the earliest moments of recognition, object concepts are tokened 'holistically' through lexical labels representing whole objects at the superordinate level, not through their constituent features. Importantly, this superordinate advantage was robust across both presentation time conditions (i.e., 50/60 ms and 190/200 ms). Also, results from both experiments showed greater accuracy for picture-word pairs projected to the right and left hemisphere, respectively, supporting a body of literature claiming a RH advantage for visual word recognition. These results persisted even after controlling for the potential of spillover information at the fovea, in Experiment 2. Furthermore, results revealed greater accuracy for stimuli projected through ipsilateral visual pathways—casting doubts on the proposal that contralateral pathways lead to processing advantages due to containing a larger density of retinal ganglion cells.

In light of these results, it would be important to briefly revisit the predictions of the theories we presented in the introduction and how they fare. We postulated that a theory of concepts, which relies on accessing constituent features—in particular, features that are taken to carry greater weight, akin to the Prototype theory—should lead to greater accuracy and faster responses when pictures are paired with a high-prototypical feature, regardless of the presentation duration. Conversely, at the other end of the spectrum, we postulated that theories relying on a direct link between an 'atomic' concept and full object referents should lead to greater accuracy and faster responses to picture-word pairs when words represent whole object referents—namely, to pictures paired with basic level labels (e.g., dog → DOG). The pattern of results we obtained partially support the atomism view. While we did not predict that superordinate labels would yield greater accuracy and shorter RTs than the other target types, in the 50/60 ms presentation time condition, these results nevertheless support the atomism view of concept representation. In particular, our results seem to suggest that what is represented at the core of concepts is non-decompositional information, given that superordinate and basic level labels both select whole objects as their referent. Otherwise, one would have expected participants' responses to be faster and more accurate when pictures were paired with high-prototypical features at both presentation time conditions. Additionally, since superordinate and basic level labels led to faster and more accurate responses than high-prototypical features, at both presentation timepoints, it is unclear what is the role features given that they did not seem to aid the process of conceptual tokening. It is also difficult for concept theories relying on features to establish an analytic/synthetic distinction—that is, to determine which features are tokened as a function of the core concept, from those that arise as a function of synthetic entailments, that is, those that are contingent on experience. While we cannot determine whether the high-prototypical (e.g., BARK) and low-prototypical features (e.g., FUR) employed in the present study are analytic or synthetic features of the concept (e.g., DOG), it could be the case that a concept is a bundle of features, and that one such 'feature' is the essential property, viz., that of *being* a dog, or the *dogness* property. Thus, we can conceive of a conceptual system that has DOG as the triggering referent and as the entry point of a set of features (e.g., BARK, TAIL, FUR, PAWS). If this were the case, we should have observed prototypicality effects (i.e., greater accuracy and short RTs for high-prototypical features) in the 190/200 ms presentation time condition. However, the results do not support this interpretation. Rather, basic level (e.g., *dog*) and superordinate labels (e.g., *animal*) still yielded the greatest accuracy and the shortest RTs, in the 190/200 ms presentation time condition.

Finally, we should return to the main overarching question of the present study: *what* kind of information is accessed when we token object concepts? This question bears on the nature of the representation that is accessed when tokening a concept. Altogether, results of the present study seem to support a view of conceptual representation that is, in principle, atomistic. We make this proposal because, according to the main brand of atomism (Fodor, 1998), concepts are individuated by their referents through some form of 'nomic, mind-world relation' (Fodor, 1998, p. 121). That is, there is a lawful, causal link between a representation and its referent, say, an object or event in the world. Consequently, conceptual representations are said to have no constituent structure—no *necessary* properties. The results we obtained are partially in line with this view: pictures that are paired with lexical labels representing 'whole' referent objects—namely, superordinate and basic level labels—seem to have preferential access over labels representing conceptual features. Interestingly, our results also seem to suggest that the initial access to object concepts does not seem to be specific to the *token* object (e.g., DOG). Rather, the content that is initially accessed by object concepts seems to relate, more broadly, to object *type*—that is, category information. Together, this would suggest that conceptual tokening may prioritize category information (i.e., *type*), with information specific to the object (i.e., *token*) immediately following, and information relating to concept features only being accessed once object token information is entertained—to wit, ANIMAL > DOG> {DOG PROPERTIES}. It is important to note that we do not take these properties—the likes of ANIMAL, DOG, and {DOG PROPERTIES}—to be analytic entailments, in the sense that they are not proper inferences whose consequent is by necessity entailed by the antecedent. Rather, we take them to be conceptual relations, which may be accessed through a system of inferential links. We propose that these inferential links may be principled through quasi-logical inferences in the form of meaning postulates (see (1); de Almeida & Antal, 2021; de Almeida, 1999).

(1) dog picture → ANIMAL → {*visual properties*} → DOG
$[ANIMAL(x)] \rightarrow [DOG(x)]$[9]
$[ANIMAL(x)] \rightarrow [LIVING\ THING(x)]$
$[DOG(x)] \rightarrow [BARK(x)]$
$[DOG(x)] \rightarrow [FUR(x)]$
$(\forall x\ [P(x)] \rightarrow [Q(x)])^n$

As such, while there may be privileged access to *type* information, whereby *dog* may first trigger ANIMAL—a general property of the referent—it is possible that the *token* DOG is subsequently quickly accessed through a referential link that is more informed on the nature of the referent, due to having encoded more perceptual information. This process, we propose, is similar to the computation of object representations in structural theories such as Biederman's (1987), in which low-level visual features give rise to the computation of a generalized layout (a *type*) and only then the actual object (*token*) is identified. Moreover, once ANIMAL and DOG are tokened, other properties (e.g., LIVING, ANIMATE, BARK, FUR) may then be accessed through meaning postulates, given that these properties may be within the inferential domain of ANIMAL and DOG.

While it is not clear how referential links between an object and its representation—whether it be *type* or *token*—can be extended to non-perceptual content (e.g., JUSTICE, BEAUTY, FRIEND), we speculate that these representations too can be grounded through inferential links, that is, by chains of referential and inferential connections, not unlike concepts attained by historical reference (MOSES, MESOPOTAMIA), beyond the perceptual circle (see Fodor & Pylyshyn, 2015). A similar problem arises for concepts that are lexicalized by verbs (KILL, RUN, EAT), which are perceptually unbounded and may involve the triggering of numerous type/token inferences.

[9] Notice that this is not a *logical* entailment but a representation of the link between ANIMAL and DOG triggered upon the computation of more detailed visual features of the object.

In summary, the results stemming from our study suggest that concept tokening may rely on non-decompositional processes tokening ‘whole’ objects at the superordinate level, and that conceptual feature may be processed only after concepts have been accessed. Moreover, we suggest that object concepts are represented in the brain by abstract atomic symbols carrying information about their superordinate categories or information akin to their generic lexical labels, not through their constituent or salient features. While objects might first be accessed via their primitive visual properties (i.e., lines, vertices, colour, texture, shape), these properties may not be semantically active: they contribute to the object file compilation but not to the representation of the concept to which the object file is linked initially. It is only after a general property *type* is established that the *token* object concept is accessed. Thus, we see ANIMAL before we know it is DOG.

The results of our study also contribute to an understanding of the neuro-cognitive resources underlying our ability to interpret what we see, thus providing us with crucial insights on how concepts are organized in the brain, and how they interact with other cognitive systems. Given that concepts are the basic elements of meaning, understanding their nature and role in cognitive processes is key to understanding how the brain stores and processes information.

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Appendix A

List of Experimental Materials as well as the Cue Validity, Distinctiveness, and Naming Agreement Values Associated with Each Picture

| ITEM | BASIC LEVEL LABEL | COUNT | SUPERORDINATE FEATURE | COUNT | HIGH_PROTOTYPICAL FEATURE | FEATURE_TYPE | COUNT | CV | DISTINCT | LOW_PROTOTYPICAL FEATURE | FEATURE_TYPE | COUNT | CV | DISTINCT | L/NL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| accordion | accordion | 90 | instrument | 86 | key | part-to-whole | 36 | 0.224 | 0.100 | sound | sound | 14 | 0.091 | 0.050 | NL |
| airplane | plane | 93 | transport | 47 | fly | function | 43 | 0.121 | 0.038 | engine | part-to-whole | 19 | 0.275 | 0.143 | NL |
| ant | ant | 96 | insect | 86 | small | dimension | 43 | 0.026 | 0.006 | black | colour | 18 | 0.073 | 0.017 | L |
| apple | apple | 100 | fruit | 91 | red | colour | 61 | 0.086 | 0.023 | juicy | taste | 26 | 0.070 | 0.048 | L |
| asparagus | asparagus | 83 | vegetable | 74 | green | colour | 83 | 0.100 | 0.027 | long | dimension | 31 | 0.025 | 0.008 | L |
| axe | axe | 91 | tool | 89 | sharp | tactile/shape | 66 | 0.110 | 0.020 | metal | substance | 31 | 0.014 | 0.010 | NL |
| ball | ball | 100 | toy | 88 | round | shape | 59 | 0.049 | 0.007 | rubber | substance | 30 | 0.309 | 0.333 | NL |
| balloon | balloon | 100 | toy | 57 | rubber | substance | 35 | 0.361 | 0.067 | light | quality | 17 | 0.033 | 0.009 | NL |
| banana | banana | 100 | fruit | 91 | yellow | colour | 87 | 0.184 | 0.024 | peel | part-to-whole | 41 | 0.506 | 0.091 | L |
| bear | bear | 100 | animal | 88 | fur | substance | 49 | 0.084 | 0.025 | danger | *quality* | 18 | 0.066 | 0.019 | L |
| bed | bed | 100 | furniture | 87 | soft | quality | 40 | 0.052 | 0.009 | pillow | concept-association | 20 | 0.870 | 0.500 | NL |
| bee | bee | 91 | insect | 85 | wing | body part | 38 | 0.094 | 0.050 | yellow | colour | 18 | 0.038 | 0.024 | L |
| belt | belt | 92 | clothing | 48 | leather | substance | 59 | 0.176 | 0.037 | long | dimension | 24 | 0.019 | 0.008 | NL |
| bicycle | bicycle | 63 | transport | 45 | wheel | part-to-whole | 61 | 0.126 | 0.059 | seat | part-to-whole | 27 | 0.144 | 0.067 | NL |
| bird | bird | 69 | animal | 66 | small | dimension | 50 | 0.030 | 0.006 | chirp | sound | 12 | 0.462 | 0.250 | L |
| boot | boot | 97 | clothing | 53 | zipper | part-to-whole | 41 | 0.621 | 0.200 | warm | function | 17 | 0.028 | 0.019 | NL |
| bottle | bottle | 98 | container | 38 | glass | substance | 79 | 0.167 | 0.045 | clear | quality | 23 | 0.173 | 0.043 | NL |
| bread | bread | 99 | food | 97 | soft | tactile | 41 | 0.053 | 0.009 | loaf | substance | 18 | 1.000 | 1.000 | NL |
| broom | broom | 100 | tool | 39 | bristle | part-to-whole | 50 | 0.230 | 0.200 | wooden | material/substance? | 18 | 0.021 | 0.019 | NL |
| brush | brush | 100 | tool | 35 | bristle | part-to-whole | 71 | 0.327 | 0.200 | hair | part-to-whole | 23 | 0.097 | 0.023 | NL |
| bus | bus | 100 | vehicle | 46 | wheel | part-to-whole | 32 | 0.066 | 0.059 | driver | concept-association | 15 | 0.882 | 0.333 | NL |
| butterfly | butterfly | 100 | insect | 83 | wing | body part | 55 | 0.136 | 0.050 | antenna | body part | 27 | 0.208 | 0.083 | L |
| cake | cake | 100 | food | 71 | sweet | taste | 56 | 0.099 | 0.032 | frost | part-to-whole | 25 | 0.926 | 0.500 | NL |
| camel | camel | 99 | animal | 91 | hump | body part | 67 | 0.971 | 0.333 | tall | dimension | 21 | 0.052 | 0.019 | L |
| candle | candle | 100 | light | 41 | wax | substance | 70 | 0.814 | 0.200 | light | function | 32 | 0.062 | 0.009 | NL |
| cannon | cannon | 98 | weapon | 81 | wheel | part-to-whole | 34 | 0.070 | 0.059 | danger | quality | 16 | 0.058 | 0.019 | NL |
| car | car | 98 | vehicle | 52 | wheel | part-to-whole | 42 | 0.087 | 0.059 | fast | quality | 20 | 0.033 | 0.012 | NL |
| carrot | carrot | 100 | vegetable | 81 | orange | colour | 90 | 0.336 | 0.048 | long | dimension | 21 | 0.017 | 0.008 | L |
| cat | cat | 99 | animal | 83 | fur | substance | 40 | 0.069 | 0.025 | purr | sound | 14 | 0.933 | 0.500 | L |
| celery | celery | 83 | vegetable | 76 | green | colour | 84 | 0.102 | 0.027 | crunch | sound | 26 | 0.211 | 0.053 | L |
| chair | chair | 100 | furniture | 89 | leg | part-to-whole | 41 | 0.062 | 0.015 | back | part-to-whole | 21 | 0.538 | 0.125 | NL |
| cherry | cherry | 97 | fruit | 90 | red | colour | 80 | 0.113 | 0.023 | stem | part-to-whole | 34 | 0.126 | 0.032 | L |
| chicken | chicken | 81 | animal | 55 | feather | substance | 57 | 0.126 | 0.091 | beak | body part | 25 | 0.102 | 0.077 | L |
| church | church | 93 | building | 78 | steeple | part-to-whole | 30 | 0.968 | 0.500 | worship | function | 14 | 0.933 | 0.500 | NL |
| coat | coat | 64 | clothing | 94 | warm | function | 50 | 0.083 | 0.019 | sleeve | part-to-whole | 12 | 0.098 | 0.143 | NL |
| corn | corn | 99 | vegetable | 63 | yellow | colour | 68 | 0.143 | 0.024 | sweet | taste | 25 | 0.044 | 0.032 | L |
| cow | cow | 95 | animal | 87 | milk | function | 49 | 0.605 | 0.091 | udder | body part | 25 | 1.000 | 1.000 | L |
| deer | deer | 97 | animal | 88 | antler | body part | 49 | 0.925 | 0.250 | hoof | body part | 22 | 0.125 | 0.100 | L |
| dog | dog | 100 | animal | 84 | bark | sound | 38 | 0.066 | 0.025 | fur | substance | 14 | 0.269 | 0.038 | L |
| doll | doll | 74 | toy | 72 | small | dimension | 29 | 0.017 | 0.006 | cute | quality | 15 | 0.107 | 0.026 | NL |
| donkey | donkey | 89 | animal | 89 | tail | body part | 25 | 0.039 | 0.024 | gray | colour | 13 | 0.087 | 0.026 | L |
| dress | dress | 94 | clothing | 96 | long | dimension | 36 | 0.029 | 0.008 | woman | concept-association | 16 | 0.035 | 0.111 | NL |
| dresser | dresser | 76 | furniture | 85 | drawer | part-to-whole | 46 | 0.465 | 0.333 | heavy | quality | 20 | 0.026 | 0.009 | NL |
| drum | drum | 99 | instrument | 86 | loud | sound | 49 | 0.082 | 0.016 | music | sound | 23 | 0.076 | 0.067 | NL |
| duck | duck | 96 | bird | 52 | feather | substance | 56 | 0.124 | 0.091 | webbed | body part | 20 | 0.408 | 0.125 | L |
| eagle | eagle | 85 | bird | 68 | feather | substance | 36 | 0.080 | 0.091 | talon | body part | 16 | 0.762 | 0.500 | L |
| ear | ear | 100 | body | 58 | hear | function | 54 | 0.931 | 0.250 | lobe | body part | 21 | 0.913 | 0.333 | L |
| elephant | elephant | 100 | animal | 87 | large | dimension | 49 | 0.057 | 0.008 | big | dimension | 18 | 0.043 | 0.009 | L |
| eye | eye | 100 | body | 51 | pupil | body part | 29 | 1.000 | 1.000 | vision | function | 14 | 0.452 | 0.200 | L |
| fish | fish | 94 | animal | 67 | fin | body part | 44 | 0.629 | 0.200 | water | concept-association | 15 | 0.047 | 0.022 | L |
| flower | flower | 97 | plant | 65 | petal | part-to-whole | 47 | 0.922 | 0.333 | pretty | quality | 17 | 0.131 | 0.026 | L |
| flute | flute | 87 | instrument | 90 | metal | substance | 44 | 0.020 | 0.010 | key | part-to-whole | 14 | 0.087 | 0.100 | NL |
| fly | fly | 95 | insect | 83 | wing | body part | 48 | 0.119 | 0.050 | annoy | quality | 24 | 0.436 | 0.050 | L |
| foot | foot | 96 | body | 63 | toe | body part | 58 | 0.707 | 0.125 | ankle | body part | 26 | 0.722 | 0.250 | L |
| fork | fork | 100 | utensil | 55 | metal | substance | 53 | 0.024 | 0.010 | prong | part-to-whole | 24 | 0.333 | 0.167 | NL |
| fox | fox | 79 | animal | 86 | fur | substance | 43 | 0.074 | 0.025 | sly | *quality* | 18 | 0.900 | 0.333 | L |
| frog | frog | 97 | animal | 55 | green | colour | 52 | 0.063 | 0.027 | jump | motion | 24 | 0.203 | 0.067 | L |
| giraffe | giraffe | 98 | animal | 89 | tall | dimension | 75 | 0.187 | 0.019 | neck | body part | 37 | 0.339 | 0.071 | L |
| glove | glove | 100 | clothing | 66 | warm | function | 53 | 0.088 | 0.019 | hand | function | 19 | 0.110 | 0.048 | NL |
| goat | goat | 97 | animal | 86 | horn | body part | 50 | 0.242 | 0.067 | hoof | body part | 25 | 0.143 | 0.100 | L |
| gorilla | gorilla | 77 | animal | 80 | strong | quality | 44 | 0.142 | 0.014 | black | colour | 22 | 0.089 | 0.017 | L |
| grapes | grapes | 100 | fruit | 91 | sweet | taste | 39 | 0.069 | 0.032 | vine | concept-association | 11 | 0.579 | 0.167 | L |
| guitar | guitar | 100 | instrument | 90 | string | part-to-whole | 78 | 0.192 | 0.043 | music | sound | 33 | 0.110 | 0.067 | NL |

| ITEM | BASIC LEVEL LABEL | COUNT | SUPERORDINATE FEATURE | COUNT | HIGH_PROTOTYPICAL FEATURE | FEATURE_TYPE | COUNT | CV | DISTINCT | LOW_PROTOTYPICAL FEATURE | FEATURE_TYPE | COUNT | CV | DISTINCT | L/NL |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| gun | gun | 71 | weapon | 69 | metal | substance | 44 | 0.020 | 0.010 | barrel | part-to-whole | 15 | 0.625 | 0.200 | NL |
| hammer | hammer | 99 | tool | 97 | metal | substance | 47 | 0.021 | 0.010 | nail | concept-association | 20 | 0.081 | 0.071 | NL |
| hand | hand | 99 | body | 64 | finger | body part | 62 | 0.380 | 0.067 | skin | body part | 14 | 0.058 | 0.027 | L |
| harp | harp | 96 | instrument | 87 | string | part-to-whole | 65 | 0.160 | 0.043 | music | sound | 29 | 0.096 | 0.067 | NL |
| horse | horse | 99 | animal | 88 | mane | body part | 35 | 0.347 | 0.200 | tall | dimension | 18 | 0.045 | 0.019 | L |
| iron | iron | 99 | appliance | 44 | hot | temperature | 66 | 0.207 | 0.036 | metal | substance | 33 | 0.015 | 0.010 | NL |
| kangaroo | kangaroo | 100 | animal | 81 | pouch | body part | 50 | 0.943 | 0.333 | tail | body part | 23 | 0.036 | 0.024 | L |
| kite | kite | 100 | toy | 72 | string | part-to-whole | 57 | 0.140 | 0.043 | light | quality | 17 | 0.033 | 0.009 | NL |
| ladder | ladder | 98 | tool | 76 | tall | dimension | 38 | 0.095 | 0.019 | long | substance | 16 | 0.013 | 0.008 | NL |
| leaf | leaf | 99 | plant | 45 | green | colour | 45 | 0.054 | 0.027 | fall | concept-association | 21 | 0.656 | 0.111 | L |
| lemon | lemon | 95 | fruit | 89 | yellow | colour | 77 | 0.162 | 0.024 | juicy | taste | 20 | 0.054 | 0.048 | L |
| lion | lion | 99 | animal | 86 | mane | body part | 45 | 0.446 | 0.200 | fur | substance | 20 | 0.034 | 0.025 | L |
| mitten | mitt | 81 | clothing | 68 | warm | function | 83 | 0.138 | 0.019 | soft | tactile | 27 | 0.035 | 0.009 | NL |
| monkey | monkey | 91 | animal | 79 | tail | body part | 44 | 0.068 | 0.024 | smart | *quality* | 15 | 0.192 | 0.030 | L |
| motorcycle | motorcycle | 93 | vehicle | 51 | wheel | part-to-whole | 46 | 0.095 | 0.059 | danger | quality | 18 | 0.066 | 0.019 | NL |
| nail | nail | 98 | tool | 55 | metal | substance | 60 | 0.027 | 0.010 | small | dimension | 22 | 0.013 | 0.006 | NL |
| necklace | necklace | 91 | jewelry | 73 | pearl | concept-association | 42 | 0.808 | 0.500 | expensive | quality | 20 | 0.175 | 0.027 | NL |
| onion | onion | 99 | vegetable | 80 | round | shape | 24 | 0.020 | 0.008 | root | part-to-whole | 10 | 0.204 | 0.143 | L |
| orange | orange | 87 | fruit | 88 | orange | colour | 49 | 0.183 | 0.048 | peel | part-to-whole | 15 | 0.185 | 0.091 | L |
| ostrich | ostrich | 90 | bird | 61 | feather | substance | 46 | 0.102 | 0.091 | beak | part-to-whole | 20 | 0.082 | 0.077 | L |
| owl | owl | 100 | bird | 61 | feather | substance | 46 | 0.102 | 0.091 | beak | body part | 22 | 0.090 | 0.077 | L |
| pants | pants | 98 | clothing | 98 | long | dimension | 47 | 0.038 | 0.008 | leg | part-to-whole | 18 | 0.027 | 0.015 | NL |
| peach | peach | 84 | fruit | 86 | sweet | taste | 53 | 0.093 | 0.032 | round | shape | 23 | 0.019 | 0.008 | L |
| peacock | peacock | 96 | bird | 62 | color | visual | 65 | 0.136 | 0.014 | beautiful | quality | 17 | 0.130 | 0.019 | L |
| pear | pear | 97 | fruit | 86 | green | colour | 52 | 0.063 | 0.027 | stem | part-to-whole | 14 | 0.052 | 0.032 | L |
| penguin | penguin | 100 | animal | 57 | black | colour | 32 | 0.130 | 0.017 | flightless | motion | 16 | 0.533 | 0.250 | L |
| pepper | pepper | 94 | vegetable | 72 | green | colour | 49 | 0.059 | 0.027 | red | colour | 21 | 0.030 | 0.023 | L |
| piano | piano | 100 | instrument | 87 | key | part-to-whole | 55 | 0.342 | 0.100 | music | sound | 28 | 0.093 | 0.067 | NL |
| pig | pig | 96 | animal | 88 | pink | colour | 34 | 0.327 | 0.043 | heavy | dimension | 12 | 0.016 | 0.009 | L |
| pineapple | pineapple | 100 | fruit | 89 | sweet | taste | 51 | 0.090 | 0.032 | juicy | taste | 25 | 0.068 | 0.048 | L |
| pliers | pliers | 83 | tool | 98 | metal | substance | 70 | 0.031 | 0.010 | grip | tactile | 27 | 0.338 | 0.053 | NL |
| plug | plug | 92 | electric | 58 | prong | part-to-whole | 44 | 0.611 | 0.167 | cord | concept-association | 22 | 0.293 | 0.111 | NL |
| rabbit | rabbit | 89 | animal | 89 | ear | body part | 42 | 0.255 | 0.036 | hop | motion | 21 | 0.273 | 0.200 | L |
| raccoon | raccoon | 96 | animal | 90 | fur | substance | 31 | 0.053 | 0.025 | small | dimension | 13 | 0.008 | 0.006 | L |
| refrigerator | fridge | 100 | appliance | 77 | cold | temperature | 71 | 0.297 | 0.020 | food | concept-association | 22 | 0.104 | 0.018 | NL |
| rhino | rhino | 100 | animal | 89 | horn | body part | 74 | 0.357 | 0.067 | large | dimension | 34 | 0.039 | 0.008 | L |
| ring | ring | 100 | jewelry | 75 | round | shape | 38 | 0.031 | 0.008 | expensive | quality | 16 | 0.140 | 0.027 | NL |
| rocking | chair | 81 | furniture | 88 | rock | function | 55 | 0.705 | 0.167 | wood | substance | 28 | 0.036 | 0.015 | NL |
| sandwich | sandwich | 99 | food | 99 | bread | part-to-whole | 58 | 0.682 | 0.167 | taste | taste | 28 | 0.088 | 0.023 | NL |
| saw | saw | 100 | tool | 96 | sharp | tactile/shape | 67 | 0.112 | 0.020 | handle | part-to-whole | 31 | 0.028 | 0.015 | NL |
| sheep | sheep | 79 | animal | 86 | wool | substance | 64 | 0.451 | 0.059 | white | colour | 27 | 0.051 | 0.014 | L |
| shirt | shirt | 99 | clothing | 100 | button | part-to-whole | 47 | 0.159 | 0.048 | soft | quality | 13 | 0.017 | 0.009 | NL |
| shoe | shoe | 98 | clothing | 68 | lace | part-to-whole | 52 | 0.732 | 0.111 | heel | part-to-whole | 24 | 0.348 | 0.167 | NL |
| skirt | skirt | 74 | clothing | 95 | long | dimension | 51 | 0.041 | 0.008 | fabric | substance | 19 | 0.113 | 0.037 | NL |
| skunk | skunk | 99 | animal | 88 | smell | smell | 43 | 0.173 | 0.023 | stripe | visual | 22 | 0.087 | 0.063 | L |
| snail | snail | 97 | animal | 55 | slime | quality | 71 | 0.573 | 0.071 | small | dimension | 18 | 0.011 | 0.006 | L |
| sock | sock | 100 | clothing | 95 | warm | function | 57 | 0.095 | 0.019 | cotton | material/substance? | 25 | 0.214 | 0.043 | NL |
| spoon | spoon | 100 | utensil | 46 | metal | substance | 61 | 0.027 | 0.010 | handle | part-to-whole | 22 | 0.020 | 0.015 | NL |
| squirrel | squirrel | 99 | animal | 86 | fur | substance | 36 | 0.062 | 0.025 | cute | *quality* | 11 | 0.079 | 0.026 | L |
| sweater | sweater | 79 | clothing | 97 | warm | function | 77 | 0.128 | 0.019 | soft | tactile | 27 | 0.035 | 0.009 | NL |
| table | table | 99 | furniture | 91 | leg | part-to-whole | 45 | 0.068 | 0.015 | sturdy | quality | 17 | 0.071 | 0.012 | NL |
| tennis | racket | 97 | sport | 59 | handle | part-to-whole | 36 | 0.032 | 0.015 | net | concept-association | 16 | 0.889 | 0.333 | NL |
| tie | tie | 100 | clothing | 76 | stripe | visual | 36 | 0.142 | 0.063 | business | concept-association | 12 | 0.571 | 0.250 | NL |
| tiger | tiger | 98 | animal | 86 | stripe | visual | 65 | 0.256 | 0.063 | whisker | body part | 18 | 0.122 | 0.077 | L |
| toaster | toaster | 99 | appliance | 69 | electric | quality | 38 | 0.178 | 0.059 | bread | concept-association | 19 | 0.224 | 0.167 | NL |
| tree | tree | 97 | plant | 59 | leaf | part-to-whole | 39 | 0.225 | 0.059 | branch | part-to-whole | 20 | 0.714 | 0.250 | L |
| trumpet | trumpet | 88 | instrument | 88 | loud | sound | 50 | 0.084 | 0.016 | horn | part-to-whole | 16 | 0.077 | 0.067 | NL |
| turtle | turtle | 97 | animal | 67 | shell | body part | 65 | 0.328 | 0.100 | hard | *quality* | 9 | 0.016 | 0.007 | L |
| vest | vest | 95 | clothing | 99 | button | part-to-whole | 61 | 0.206 | 0.048 | pocket | part-to-whole | 30 | 0.213 | 0.125 | NL |
| violin | violin | 78 | instrument | 86 | string | part-to-whole | 72 | 0.177 | 0.043 | music | sound | 28 | 0.093 | 0.067 | NL |
| wagon | wagon | 88 | toy | 66 | wheel | part-to-whole | 63 | 0.130 | 0.059 | metal | substance | 22 | 0.010 | 0.010 | NL |
| watch | watch | 100 | accessory | 49 | time | dimension | 42 | 0.506 | 0.111 | hand | part-to-whole | 18 | 0.104 | 0.048 | NL |
| watermelon | melon | 90 | fruit | 84 | seed | part-to-whole | 51 | 0.271 | 0.063 | green | colour | 13 | 0.016 | 0.027 | L |
| wheel | wheel | 100 | transport | 33 | round | shape | 68 | 0.056 | 0.008 | wood | substance | 23 | 0.030 | 0.015 | NL |
| zebra | zebra | 100 | animal | 89 | stripe | visual | 81 | 0.319 | 0.063 | hoof | body part | 29 | 0.166 | 0.100 | L |

Appendix B
General Guidelines and Checklist for Participating in Experiments at Home

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# Participating in experiments at home
## General Instructions

First, we would like to thank you very much for agreeing to participate in our experiments. It is thanks to the dedication of thousands of individuals like you that we are able to advance knowledge on how language and other cognitive systems work in the brain.

We normally conduct our experiments in the lab. However, due to COVID-19, we are trying to adapt to new safety measures by mimicking as much as possible the conditions under which our experiments are normally run.

The series of tasks you agreed to participate in require **full compliance with the instructions** you see before each task begins. But they also require adherence to some general guidelines on **how you set up your workspace (computer, chair, desk, ambient light, etc.)** and how you prepare yourself to participate in the tasks.

The usual setup of a testing station in the lab includes a desk with a computer monitor and a response box (with just a few buttons) or a keyboard, in a dark or dimly-lit room. Different experiments require other equipment such as noise-cancelling headphones, microphone, a chin/head rest, etc. For the tasks you will be participating in, we strongly suggest you follow the few simple guidelines we provide here. This is important because they will allow us to collect data with the least variability across individuals as possible. Of course, different participants will have different set ups but adherence to these guidelines assure us that the data we collect reflect as much as possible the experimental conditions, not those related to your particular setting.

You will be participating in a series of three tasks. Each task takes roughly 20 to 45 minutes to complete. **You will have to complete these tasks over the course of three days, completing one task per day.**

These tasks will require you to look at words, pictures, or words and pictures simultaneously. For two of the three tasks, you will need to complete the tasks, while wearing anaglyph glasses. Anaglyph glasses are similar to 3D glasses, with one blue lens and one red lens.

The series of tasks that you would participate in will require full compliance with some general guidelines on how you set up your workspace (computer, desk, light, etc.) and how you prepare yourself to participate in the tasks. All of the guidelines are clearly detailed in the set of instructions below:

**1. Dark, quiet room.** It is important that you set up your computer in a dimly-lit, if not dark room, away from direct light sources such as lamps or windows. The darker the room, the better. The room should also be quiet, away from other distractions (people, TV, phone, etc.). Please put your phone in do-not-disturb.

**2. Sit comfortably; hands comfortably reaching your keyboard.** It is important that you sit in a comfortable position. The tasks may last from 20 min to about 45 min. During this time it is important that you avoid fatigue or leg cramps or any other physical discomfort that may be caused by prolonged sitting in an improper position.

**3. Proper position in relation to your computer.** The tasks require that you sit in front of your computer screen such that the tip of your nose is at about the same height as the center of your screen. The distance may vary. If your screen is between 13 and 16'' (inches) diagonally, the tip of your nose should be about 40 cm (16 inches) from the screen. For larger computer screens this distance should be larger--from about 45 cm to a maximum of 56 cm--again, measured from the tip of your nose to the center of the screen.

**4. Only your Internet browser (Chrome, Safari, Firefox, etc.) should be on.** These tasks are time-sensitive and having other applications running together with your browser may affect the presentation rate of stimuli as well as your responses. So, please, quit all applications except your browser. Also put your computer in 'do not disturb' mode so that you don't get notifications during the experiment. Please make sure that your internet is active because the browser will be fetching stimuli to be presented to you in real time.

**5. Before you begin**. As we mentioned, each task will have its own instructions. But it is important that you prepare in advance for these tasks, in addition to complying with the three guidelines above.

5.1 **Computer/Internet** information. Please have a pencil or pen with you and fill-out the Computer and Internet Resources form that you received in your kit. It's important that you fill out that information **before** you start the tasks. In the beginning of the first task you will be required to enter that information on the electronic form, so you can copy that information from the printed form you received. You will not have the opportunity to gather that information once the tasks begin.

5.2 **Restroom!** The task may take from 20 min to 1 hour. And once it begins, ideally you should not take a 'bathroom break', though you may have the opportunity to do so if needed during short breaks programmed within the tasks.

5.3 **Anaglyph glasses with you; and how to wear them**. For the tasks that require you to wear the included anaglyph glasses, please make sure that they are on your desk. You will be prompted with instructions on when to wear them. And when you do wear them, please make sure that they are firmly positioned such that the top edges touch your eyebrows. If you wear corrective glasses, the anaglyph glasses can go over them (most models) comfortably, though you may not be able to push them all the way against your eyebrows. Just make sure that they are comfortable throughout the tasks.

**Note about safety:** The anaglyph glasses are perfectly safe to wear for several hours. They simply filter different light waves ('colors') from each eye. They have been used in experiments and, more famously, in movie theaters and science centers for over a century. The tasks we designed have short breaks and you are free to take the glasses off during those breaks, putting them on again before you continue. However, <u>if at any time you experience any discomfort, you should discontinue the experiment.</u>

**After you completed all three tasks:** We will assign credits at the end of every week. Therefore, you can expect a delay before receiving your credit.

If, at any moment, have questions regarding the experiment, please feel free to contact us at **concordia.coglab@gmail.com**. **Once again, we thank you for your participation!**

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# Participating in experiments at home
## Checklist

Here is a checklist of the things you will need to complete for this experiment.
Please be sure to do them in this order.

---

**1.** Fill out the **Computer and Internet Configuration Questionnaire.**
It is important that you complete this first as you will need to enter these values in the consent form.

I confirm that I have filled out the Computer and Internet Configuration Questionnaire:_____

**2.** Fill out the **Consent Form**.
The link to the consent form has been provided to you in the email we sent you.
Should there be any issues, you can access the consent form by typing this address:
**https://yalesurvey.ca1.qualtrics.com/jfe/form/SV_enBBib5veEaLDOC**

I confirm that I have filled out the Consent Form: ______

**3. Participate in the first task.**
The two links for this task will have also been provided to you in the email we sent you. Specifically, under "TASK ONE", be sure to click "LINK 1".
This will send you to the first part of the first task.
Once you have completed "LINK 1", please click "LINK 2".
Once you have completed both links, take a break and complete the second task the following day.

I confirm verifying in the email whether this task requires the use of anaglyphs glasses:_____

I confirm that I have completed both, LINK 1 and LINK 2: ______

**4. Participate in the second task.**
The second task requires you to complete one link.
This link has also been provided to you in the email we sent you.
Specifically, under "TASK TWO", be sure to click "LINK 3".
This will send you to the second task.
**It is important that you wear the anaglyph glasses for this task.**
Once you have completed the second task, take a break and complete the last task the following day.

I confirm that I am wearing the anaglyph glasses to complete the second task: _____
I confirm that I have completed LINK 3: ______

**5. Participate in the third task.**
The last task requires you to complete two links.
These links have been provided to you in the email we sent you.
Specifically, under “TASK THREE”, be sure to click “LINK 4”.
This will send you to the first part of the third task.
Once you have completed “LINK 4”, please click “LINK 5”.
Once you have completed both links, you have completed the experiment.

I confirm verifying in the email whether this task requires the use of anaglyphs glasses:_____

I confirm that I have completed both, LINK 4 and LINK 5: ______

**You have now completed the experiment.** Your SONA credit will be assigned to you on the weekend (Saturday or Sunday) following the day you completed the experiment.

If you have questions regarding the experiment, please feel free to contact us at **concordia.coglab@gmail.com**. **Once again, we thank you for your participation!**

Appendix C

Computer and Internet Configuration Questionnaire

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## Computer and Internet Configuration Questionnaire

Thank you for agreeing to participate in our study.

This experiment relies on time-sensitive measures (e.g., the time it takes to press a button, fast presentation of words and pictures). Therefore, we need to gather information about your computer hardware specifications and your internet resources. This will allow us to analyze the responses of all participants taking into account their computer, screen, and internet speeds.

Please take a moment to answer the following questions to the best of your knowledge. You may need some time to gather this information. But it is essential that you have these answers with you before the beginning of the experiment. Notice that, as stated in the consent form, your answers to these and other questions will be coded and they won't be traced back to you in particular. Again, this information will allow us to analyze the data from the study more accurately. If you do not know the answer to a particular question, please write "NA".

### Section 1: Computer Hardware Specifications

(a) What is the make and model of your computer (e.g., "Macbook Pro 13 early 2020", "Acer Swift 3", "Dell Inspiron 15 7000", "Lenovo thinkPad X")

________________________________________________________________

(b) What is the current RAM (memory) configuration of your computer ? (e.g., 4, 8, 16 GB)

________________________________________________________________

(c) What is your computer's operating system? (e.g., Windows 10, Linux Ubuntu 20, MacOS 10.15.7)

(d) What is the built-in display size of your monitor? (e.g., 13.3, 15 inches)

(e) What is the resolution of your monitor display? (e.g., 2560 x 1600)

(f) What is the refresh rate of your monitor (60Hz)?

(g) If you use a laptop, do you connect it to an external monitor? If so, what is the make and model of this external monitor?

## Section 2: Internet Resources

(a) Which internet company and download speed do you use? (e.g., Videotron, 100 MBPS)

(b) Which internet browser do you use? (e.g., Chrome, Firefox, Safari) We recommend using Google Chrome for this experiment.

If there are any special circumstances regarding your computer (e.g., failing keys, flickering images) or your internet connection (e.g., intermittent connection, under 20 MBPS speeds), please describe below.

Appendix D
Exploratory Analyses

**Experiment 1: Multiple regressions for cue validity and feature distinctiveness values, for high- and low prototypical features**

Results from the first set of analyses showed that, across high-prototypical feature types, a model containing cue validity and feature distinctiveness values significantly predicted participants' accuracy on congruency decisions ($F(2, 127) = 6.13$, $p = 0.003$)—although they accounted for only 8% of the variability in participants' accuracy ($_{adj}R^2 = 0.075$). Further, feature distinctiveness was found to be a marginally significant predictor for participants' accuracy ($\beta = -0.26$, $p = 0.06$), accounting for approximately 16% of the variability. However, cue validity accounted for only 3% of the variability observed in participants' accuracy ($\beta = -0.05$, $p = 0.71$), and was thus not a statistically significant predictor. Conversely, a model containing the same predictors, across low-prototypical features, was shown not to significantly predict participants accuracy ($F(2, 127) = 1.69$, $p = 0.19$), accounting for only 1% of the variability ($_{adj}R^2 = 0.011$). Further, results also showed that cue validity and feature distinctiveness values were not statistically significant individual predictors for participants' congruency accuracy ($\beta = -0.05$, $p = 0.77$; $\beta = -0.11$, $p = 0.49$, respectively; see Figures 9 and 10).

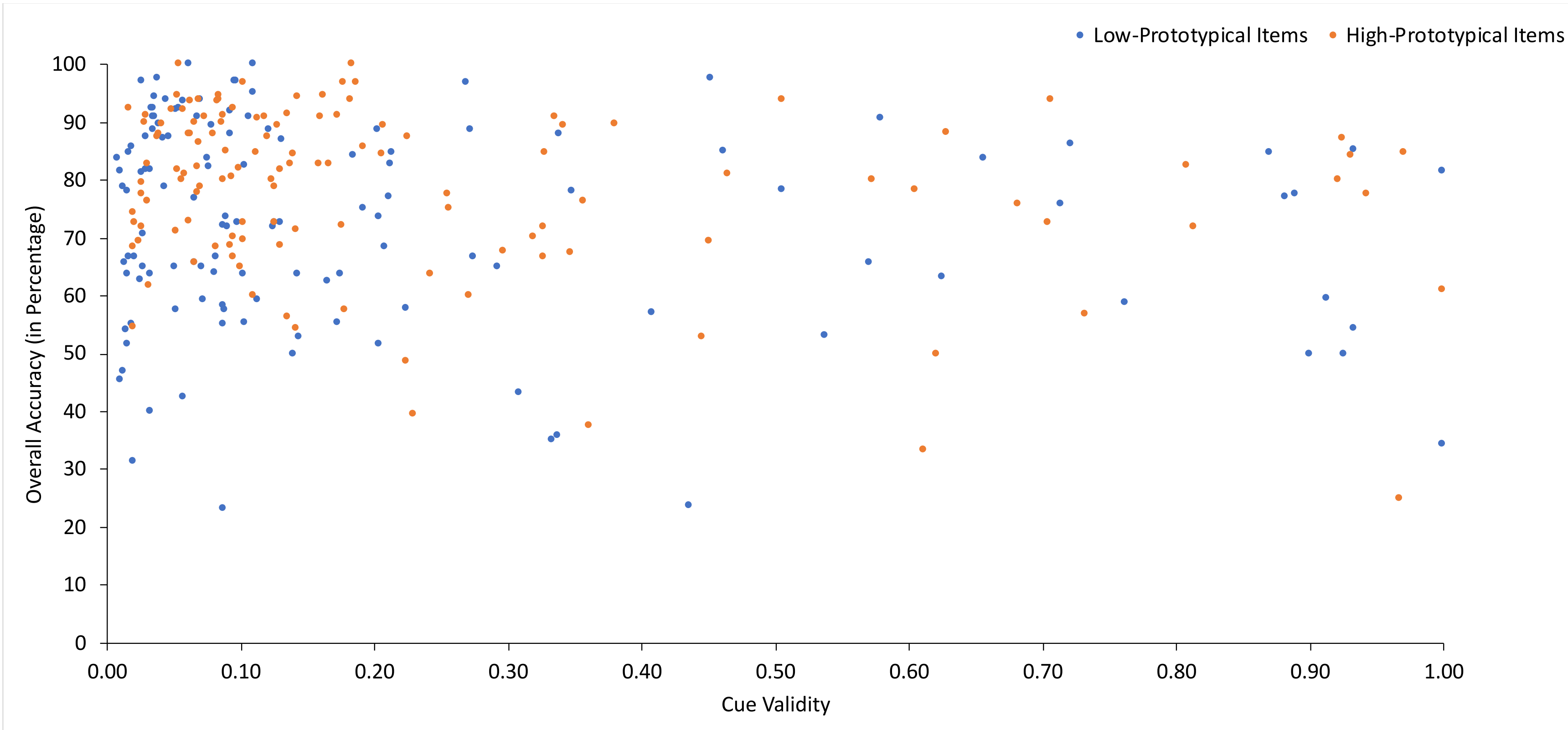


*Figure 9.* Participants' mean accuracy to congruency decisions for high- and low-prototypical features, as a function of feature cue validity values. The x-axis represents the cue validity values for target items, and the y-axis represents accuracy in percentage.

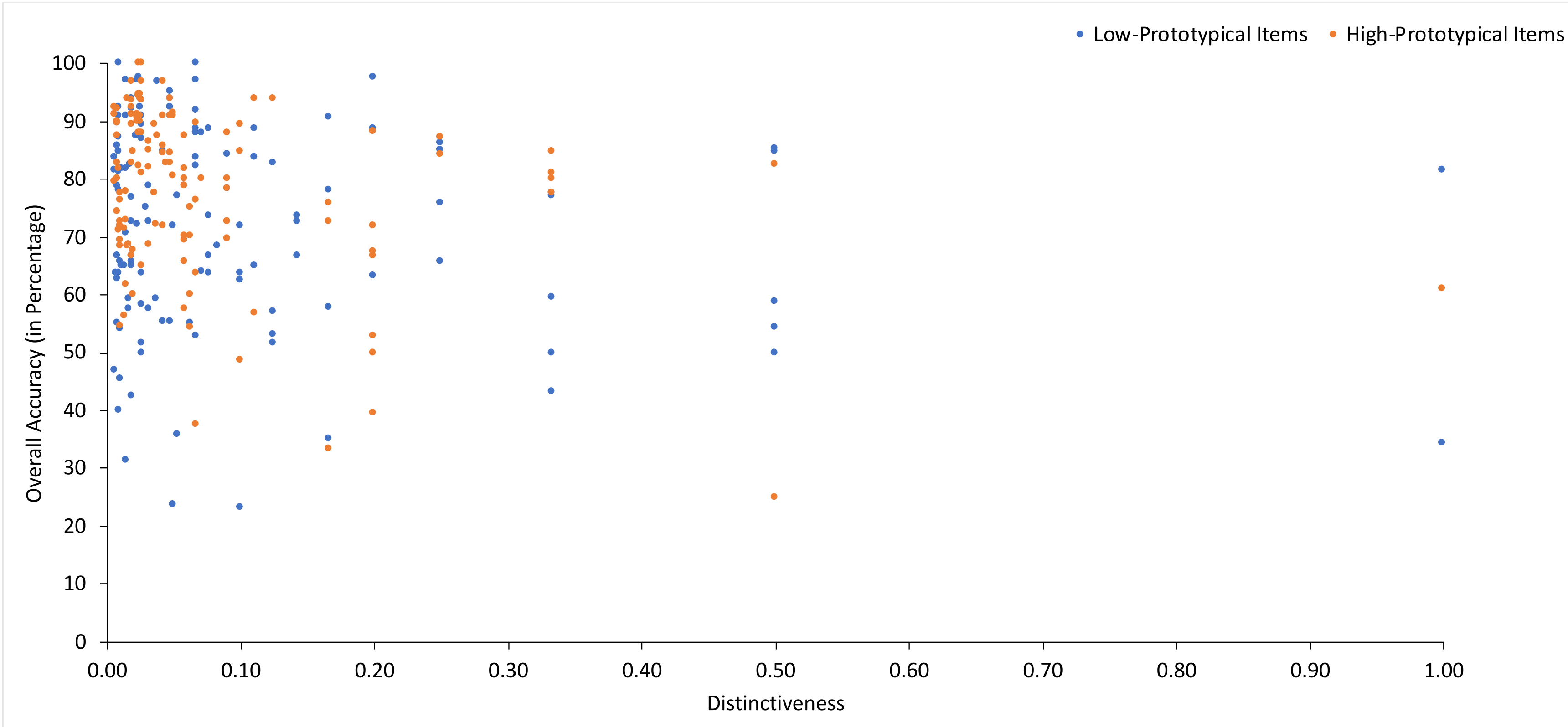


*Figure 10.* Participants' mean accuracy to congruency decisions for high- and low-prototypical features, as a function of feature distinctiveness values.

## Experiment 1: Multiple regressions for cue validity and feature distinctiveness values, for living and non-living categories

Results from the second set of analyses showed that, across both categories of living and non-living things, the models containing cue validity and feature distinctiveness values did not significantly predict participants' accuracy on congruency decisions. Further, feature cue validity and feature distinctiveness were not found to be statistically significant individual predictors for participants' congruency (see Figures 11 and 12).

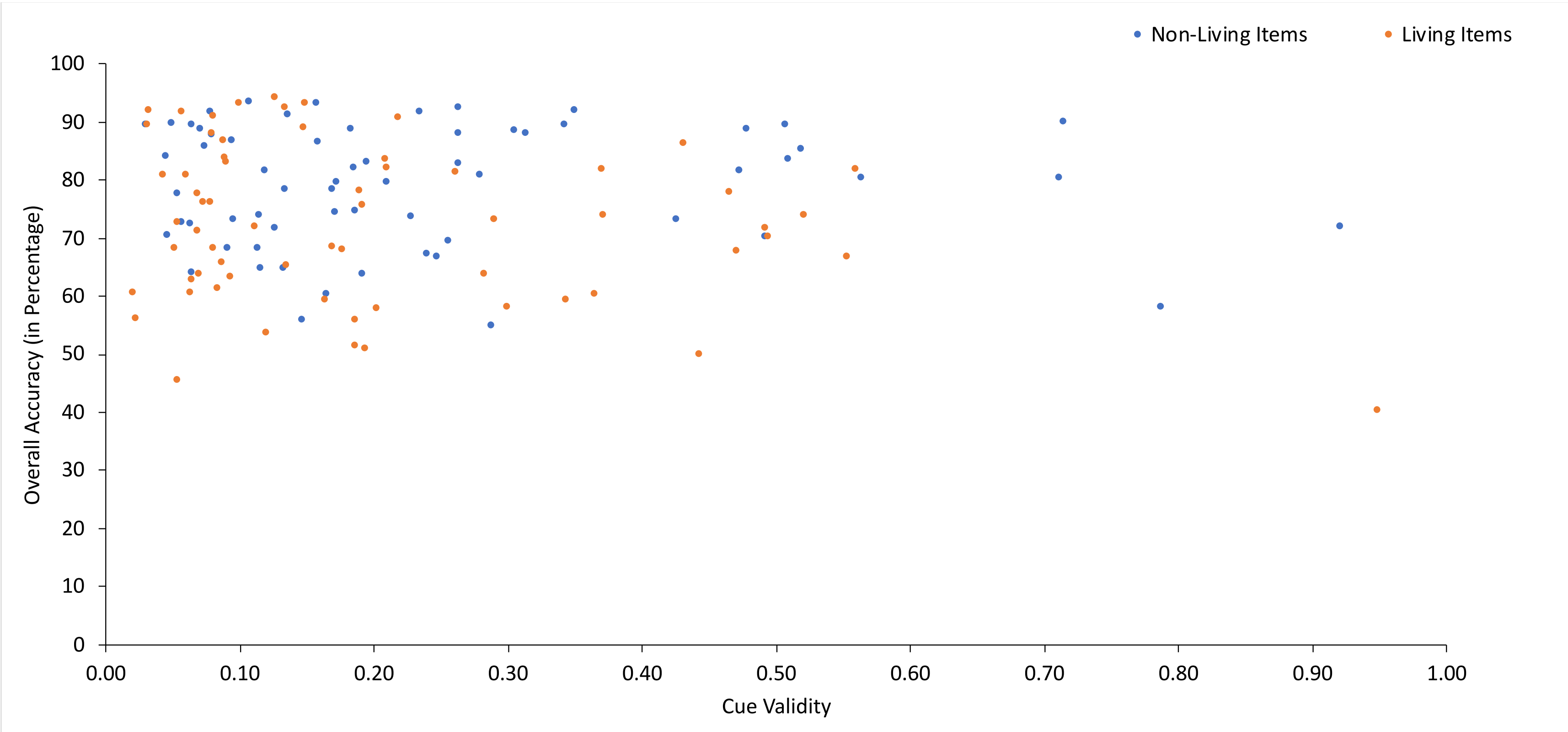


*Figure 11.* Participants' mean accuracy to congruency decisions for high- and low-prototypical features collapsed across living and nonliving categories, as a function of feature cue validity values.

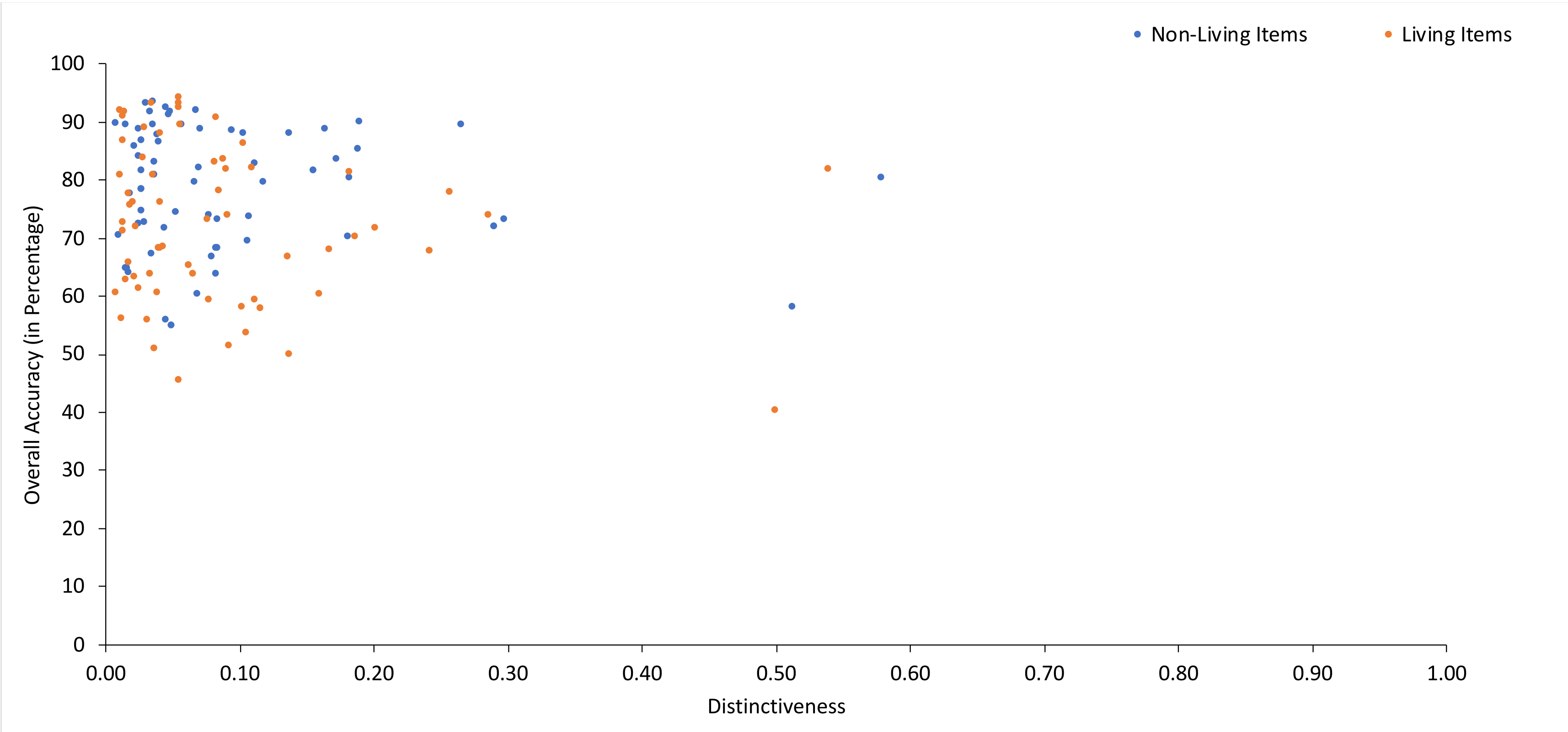


*Figure 12.* Participants' mean accuracy to congruency decisions for high- and low-prototypical features collapsed across living and nonliving categories, as a function of feature distinctiveness values.

**Experiment 2: Multiple regressions for cue validity and feature distinctiveness values, for high- and low prototypical features**

Results from the first set of analyses showed that, across high-prototypical feature types, a model containing cue validity and feature distinctiveness values significantly predicted participants' accuracy on congruency decisions ($F(2, 127) = 3.72$, $p = 0.03$)—although accounted for only 4% of the variability in participants' accuracy ($_{adj}R^2 = 0.041$). Further, cue validity and feature distinctiveness were not found to be significant individual predictors for participants' accuracy. Similarly, a model containing the same predictors, across low-prototypical features, was shown to significantly predict participants accuracy ($F(2, 127) = 5.35$, $p = 0.006$), but accounted for only 6% of the variability ($_{adj}R^2 = 0.064$). Further, results also showed that cue validity and feature distinctiveness values were not statistically significant individual predictors for participants' congruency accuracy (see Figures 13 and 14).

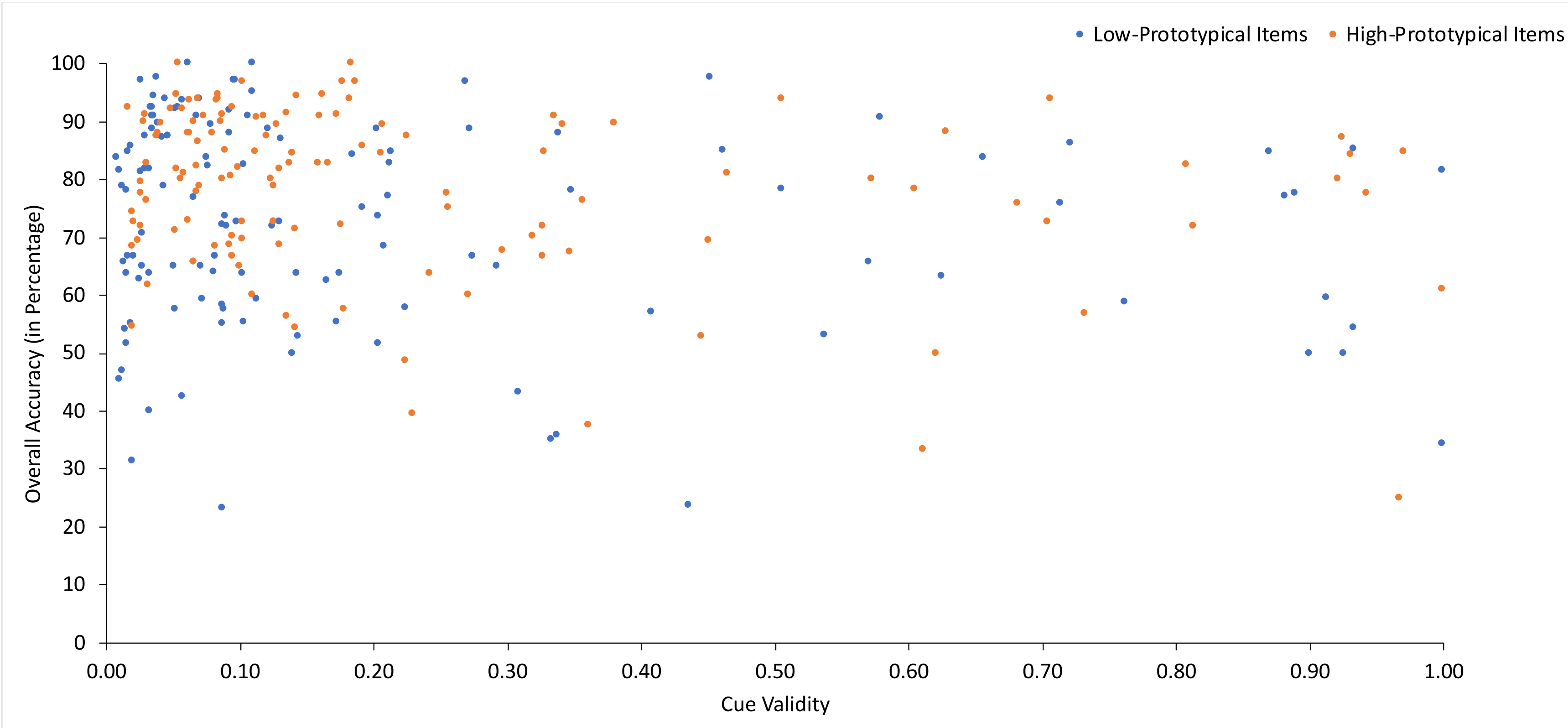


*Figure 13.* Participants' mean accuracy to congruency decisions for high- and low-prototypical features, as a function of feature cue validity values.

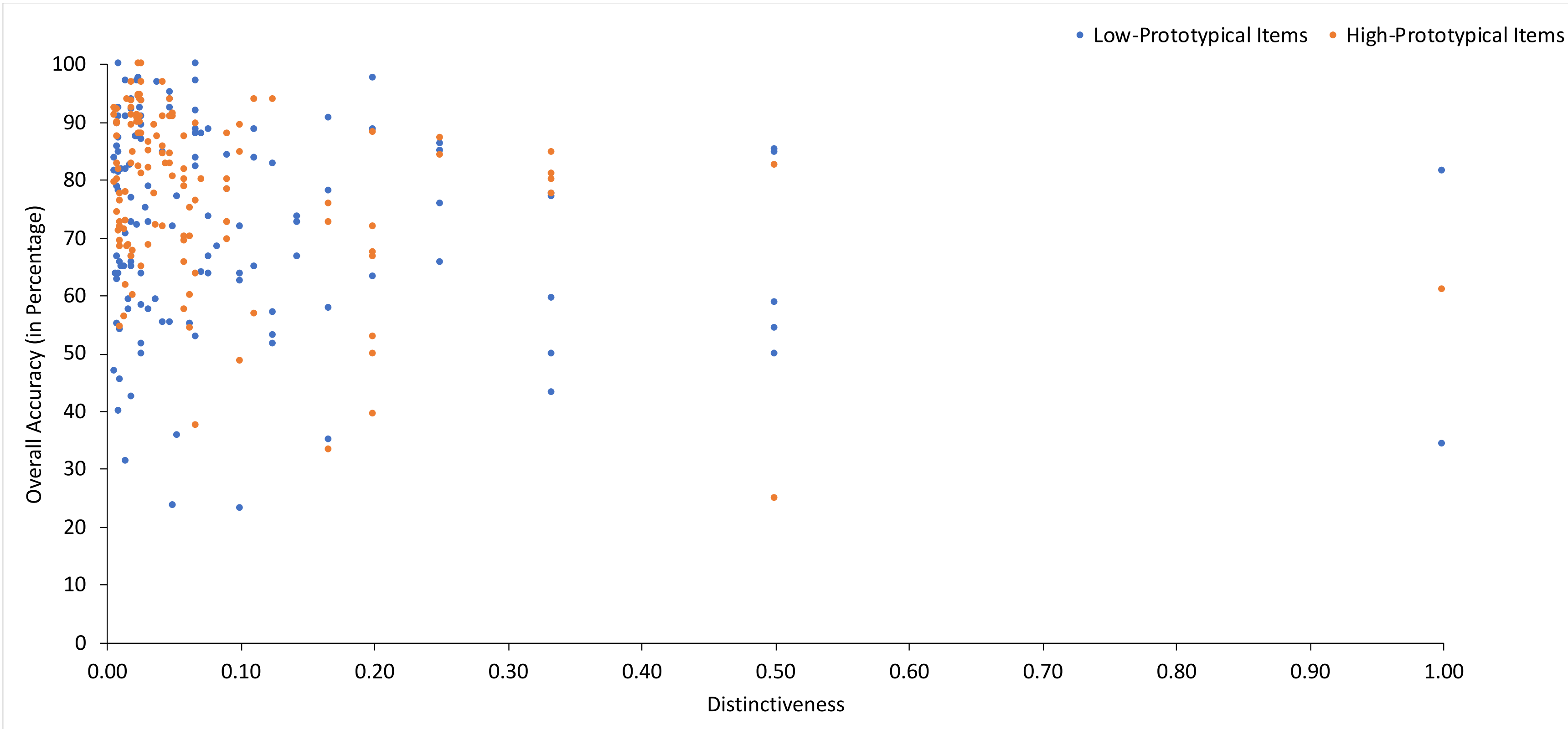


*Figure 14.* Participants' mean accuracy to congruency decisions for high- and low-prototypical features, as a function of feature distinctiveness values.

**Experiment 2: Multiple regressions for cue validity and feature distinctiveness values, for living and non-living categories**

Results from the second set of analyses showed that, across both categories of living and non-living things, the models containing cue validity and feature distinctiveness values did not significantly predict participants' accuracy on congruency decisions. Further, feature cue validity and feature distinctiveness were not found to be statistically significant individual predictors for participants' congruency (see Figures 15 and 16).

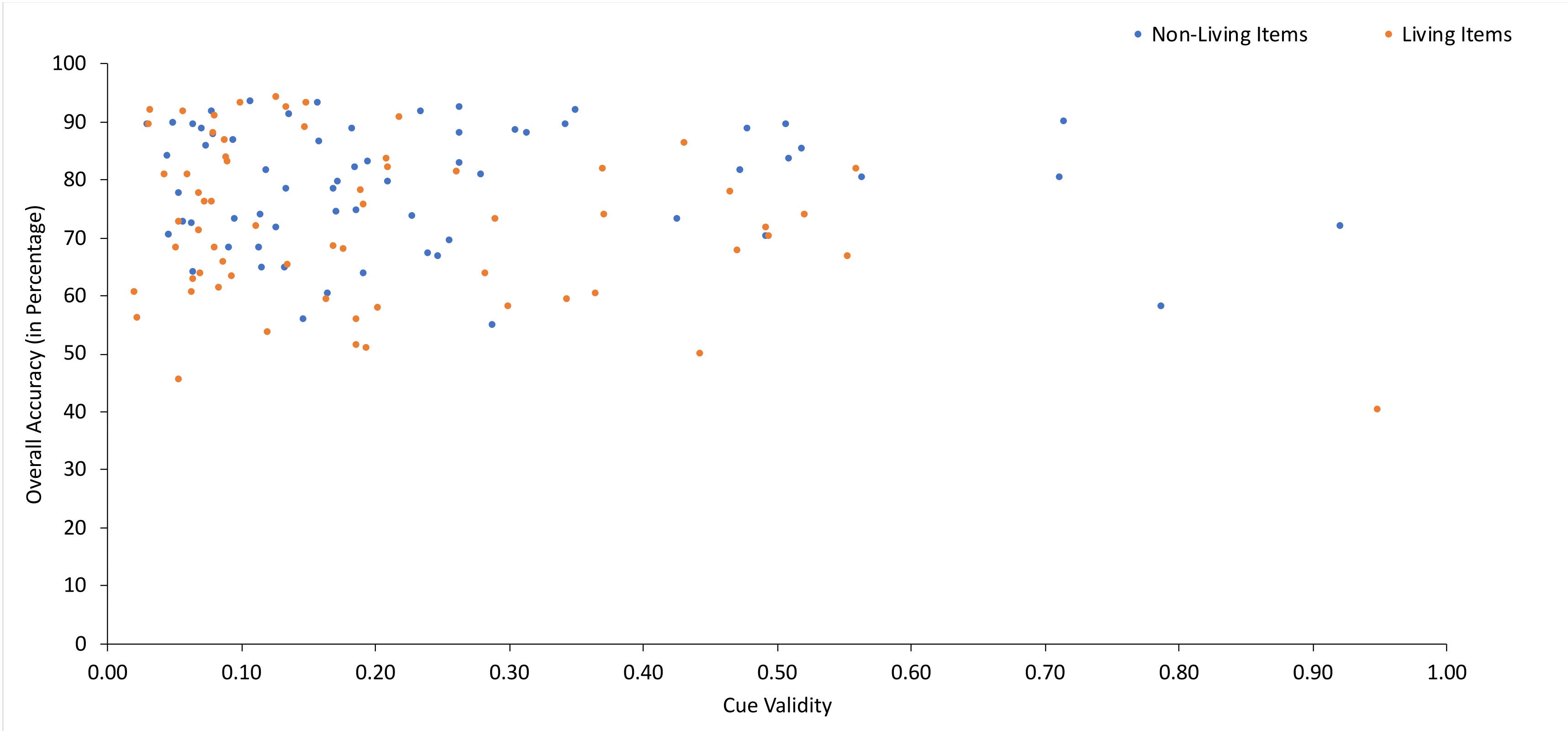


*Figure 15.* Participants' mean accuracy to congruency decisions for high- and low-prototypical features collapsed across living and nonliving categories, as a function of feature cue validity values.

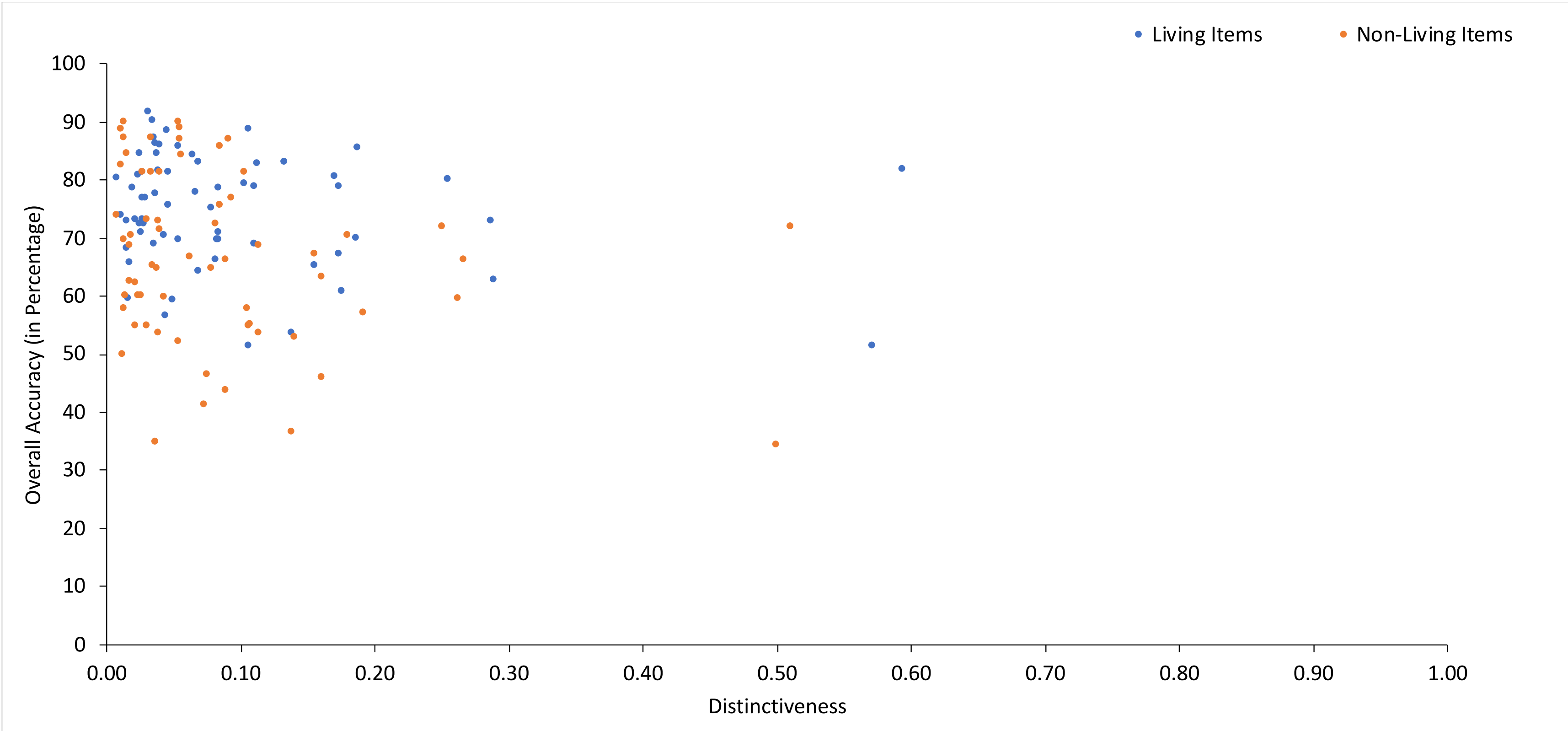


*Figure 16.* Participants' mean accuracy to congruency decisions for high- and low-prototypical features collapsed across living and nonliving categories, as a function of feature distinctiveness values.