Affordance Norms for 2825 Concrete Nouns

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Correspondence regarding this article should be addressed to Nicholas P. Maxwell, Department of Psychology, Midwestern State University, 3410 Taft Blvd, Wichita Falls, TX, 76308, United States. Email: nicholas.maxwell@msutexas.edu. The final set of affordance norms is available for download via our OSF page [LINK]. The normed dataset can also be accessed via our interactive Shiny application [LINK]. The authors thank Morgan Ballesteros, Samantha Garcia, and Madisyn Metaxas for their assistance with cleaning the final dataset.

Abstract

Objects are commonly described based on their relations to other objects (e.g., associations, semantic similarity, etc.) or their physical features (e.g., birds have wings, feathers, etc.). However, objects can also be described in terms of their actionable properties (i.e., affordances), which reflect various interactive relationships existing between actors and objects. While several normed datasets have been developed to categorize various aspects of meaning (e.g., semantic features, cue-target associations, etc.), to date, norms for affordances have not been generated. We address this limitation by developing a set of affordance norms for 2825 concrete nouns. Using an open-response format, we computed affordance strength (AFS; i.e., probability of an item eliciting a particular action response) and affordance set-size (AFSS; i.e., total number of unique action responses) for each item. Because our stimuli overlapped with Pexman et al.’s (2019) Body-Object Interaction norms, we tested whether AFSS was related to BOI, as objects with more perceived action properties may be viewed as being more interactive. Additionally, we tested the relationship between AFS and two separate measures of relatedness: Cosine similarity and forward associative strength. All analyses, however, revealed weak relationships between affordance measures and existing norms, suggesting that affordance properties reflect a separate construct.

Word Count: XXXX

*Keywords*: Affordances; Body-Object Interaction; Word Norms; Database; *R* Shiny

Affordance Norms for 2825 Highly Concrete Objects

Investigating questions surrounding memory, language, and perception requires a comprehensive understanding of what words mean, the context in which they are used, and the actionable properties of their referents. From an empirical standpoint, a word’s meaning can be operationalized in a variety of ways. In practice, however, researchers commonly rely upon measures of *semantic similarity* and *cue-target associations* to describe meaning, particularly when assessing the degree to which two words are related (see Hutchison, 2003; Kumar, 2021, for reviews). First, semantic similarity can be readily assessed in terms of the shared features between two concepts, with a greater number of shared features indicating a stronger degree of relatedness. Second, cue-target associations reflect the likelihood that exposure to a particular concept will activate information for related concepts (e.g., *mouse* – *cheese*, *mouse* – *house*, etc.; see Nelson, McEvoy, & Dennis, 2000). As a result, associations often capture a broader variety of information versus semantic features, including semantic knowledge (e.g., *mice* eat *cheese*) and linguistic information (*mouse* and *house* rhyme). Thus, while semantic features assess meaning primarily in terms of similarity, associations place a greater emphasis upon the context in which words are used.

Given the focus on semantic and associative descriptions of meaning, multiple sets of norms have been developed which aim to accurately map these concept relations. To generate these norms, participants view a series of individual concepts (typically in a written form) and list various properties of the stimuli, which vary based on the type of relatedness being assessed (e.g., a concept’s inherent features; Buchanan, Valentine, & Maxwell, 2019a; McRae, Seidenberg, Cree, & McNorgon, 2005; associated concepts; De Deyne, Navarro, Perfors, Brsybaert, & Storms, 2019; Nelson, McEvoy, & Schreiber, 2004). The past two decades have seen a proliferation of associative and semantic norm sets, with much of this growth driven by advances in computing power combined with an increased ease in large-scale data collection afforded by online methods. As a result, large sets of feature production and free association norms are available for a variety of languages, with more recent work focusing on ensuring that sufficient overlap exists between databases containing different measures (i.e., that concepts are measured on both semantic and associative variables; see Buchanan, Valentine, & Maxwell, 2019b).

While semantic and associative norms are important for assessing meaning, each measure alone is unlikely to capture all facets of a word’s meaning. As such, having multiple measures that reflect several dimensions of meaning is paramount for understanding how individuals process concept information. Recently, a growing body of research has investigated the links between knowledge acquisition and sensorimotor processing (i.e., embodied cognition; e.g., Glenberg & Gallese, 2012; see Barsalou, 1999; Glenberg, 2015, for reviews). Because sensorimotor systems are active whenever individuals process their surroundings, the embodied approach posits that perceptual and motor experiences are inextricably linked to knowledge formation, regardless of whether these experiences occur physically (i.e., actively exploring one’s environment) or mentally (i.e., recollection of past experiences, e.g., Barsalou, 2008). As such, understanding an object’s interactive properties (i.e., *affordances*; Gibson, 1977) is critical for understanding of its meaning. Unlike semantic and associative-based measures, affordances depict the various interactive relationships existing between actors and objects and may reflect a variety of common and less common actions (e.g., a chair affords sitting but also standing upon to reach an object). However, existing feature production and free association norms are not likely to capture a wide range of object uses, given that these norms emphasize and object’s constituent parts and related concepts, respectively, rather than focusing on its inherent, actionable properties.

Given the role of sensorimotor process in knowledge acquisition, Pexman and colleagues (Muraki, Siddiqui, & Pexman, 2022; Pexman, Muraki, Sidhu, Siakaluk, & Yap, 2019; Tillotson, Siakaluk, & Pexman, 2008) have attempted to quantify the degree to which individuals perceive that they can interact with a variety of objects. Recently, Pexman et al. (2019) collected body-object interaction ratings (BOI) for over 9000 English words, which were elicited via a 1-7 scale such that higher values denotated a greater degree of perceived interactivity. Consistent with an emobidied cognition approach, BOI ratings have been shown to be consistent with existing measures of semantic knowledge. Overall, the authors demonstrated that BOI was a strong predictor of responses in semantic decision tasks. Specifically, BOI facilitated lexical decision responses derived from the English Lexicon Project (Balota et al., 2007) and responses from the Calgary Semantic Decision Project (Pexman, Heard, Lloyd, & Yap, 2017). Importantly, for both tasks, any benefits of BOI on responding were only apparent when pairs were sufficiently high in BOI (i.e., BOI ratings above the midpoint). Low BOI items, which reflected more abstract concepts, were associated with responses that were both less accurate and slower. Separately, Heard, Madan, Protzner, and Pexman (2019) demonstrated that when BOI ratings are combined with three additional ratings of motor dimensionality (graspability, ease of pantomime, and number of actions), they explain a greater degree of variance in semantic processing tasks than when these ratings were used alone. Considered alongside findings from Pexman et al. (2019), it is evident that sensorimotor information is an important component of word meaning.

While BOI ratings provide researchers with a useful tool for quantifying the degree to which individuals can interact with their environment, we note two potential shortcomings which may limit their broader use First, because these ratings reflect the degree to which individuals can interact with an object, they are highly corelated with concreteness. Indeed, Pexman et al. (2019) reported that performance on lexical tasks was only facilitated for high BOI items (e.g., *chair*). For low BOI items (e.g., *autumn*), performance decreased, as by nature, an object must be tangible and concrete for it to facilitate a high degree of interaction. Thus, BOI ratings are strongly linked to an item’s concreteness. Second, because BOI reflects a quantitative rating, qualitative information regarding specific object uses, action properties, or even the context in which certain actions may occur is unavailable. While quantifying the degree of interactivity is critical given the proposed connection between sensorimotor experience and knowledge (see Barsaolou, Simmons, Barbey, & Wilson, 2003), understanding the various contexts which may facilitate or inhibit interactions is equally important. Thus, relying solely upon BOI as a measure of interactivity omits qualitative information which potentially influences actions.

**The Present Study**

Given the link between sensorimotor experience and knowledge representation, the present study sought to develop a database of affordances for concrete objects. In doing so, we utilized an open-ended response format, which allowed us to collect qualitative information regarding both potential object uses as well as the context in which these actions may occur. We framed object use in terms of perceptual affordances, such that participants were instructed to list the specific ways a given object could potentially be used or interacted with. Importantly, we incorporated an open-ended, multiple response format, such that participants were free to provide multiple uses for each object, rather than selecting from a set of pre-selected choices or typing a numerical rating. Thus, object use was captured using a method akin to feature production and free association tasks. As a result, we were able to capture a wide range of information, which maximized the potential number of affordances that could be captured for each object.

In the following sections, we first detail the creation of the affordance norm dataset and describe an interactive web-portal which was designed to facilitate exploration of this dataset. We then discuss a series of analyses which compared the affordance measures generated from this dataset with two existing measures of meaning (e.g., FAS values derived from Nelson et al., 2004’s free association norms and cosine similarity (COS) taken from Buchanan et al.’s, 2019a, feature production norms), BOI ratings (Pexman et al., 2019), and several lexical variables which could potentially influence how participants process each item (e.g., concreteness, age-of-acquisition, etc.).

**Method**

**Participants**

We recruited 3156 participants from two general settings. First, 2399 undergraduate students were recruited from 9 universities located within the northeastern, midwestern, and southern United States. The remaining 757 participants completed the study online via Prolific (www.Prolific.co). Table 1 displays final *n*s for each testing site following cleaning. All university students completed the study in exchange for partial course credit, while Prolific participants were compensated at a rate of $3.00 per 20-minute session. Prolific participants were required to have completed at least a high-school level degree or equivalent and to be native English speakers. For completeness, demographic information is reported in the Appendix (Table Ax).

**Materials**

To generate the stimuli, we initially selected 3005 nouns from the MRC psycholinguistic database (Coltheart, 1981). Words were initially selected based on concreteness, such that only high concreteness words were included (*M* concreteness ≥ 4.25). Of the 3005 words that were generated, five were randomly selected to serve as practice items. The remaining 3000 items were once randomized before being equally split into 100 lists which each contained 30 items. Overall, the final set of 3000 words had a mean concreteness rating of 4.61 (*sd* = 0.33) based on Brysbaert, Warriner, and Kuperman’s (2014) norms, mean SUBTLEX frequency rating of 2.01 (*sd* = .87; Brysbaert & New, 2009), and a mean BOI rating of 5.18 (*sd* = 0.60; Pexman et al., 2019).

**Procedure**

Across testing sites, data collection occurred online using Collector, an open-source platform for conducting web-based psychological experiments (Garcia & Kornell, 2015). Prior to beginning the norming task, participants were informed that they would be viewing a series of object words and that they would be required to list as many uses for each object as they could reasonably generate. Participants were reminded that a single object typically has multiple uses and were encouraged to list multiple object uses when possible. To illustrate this point, the word *ball* was provided as an example, with *throw*, *bounce*, and *step on* all provided as examples of potential affordances. The complete set of instructions is available at [OSF link].

After receiving the instructions, participants completed a set of five practice items, which familiarized them with the norming task. For each trial, a cue word was presented in the center of the screen, and participants were instructed to type possible affordances into a textbox located directly below the word. To maximize potential affordances, participants were not given specific instructions on how to format their responses (i.e., tense, single words vs. phrases, etc.) with the exception that they were instructed to separate each unique affordance with a comma. Thus, participants were allowed to respond to the cue with individual words, phrases, or full sentences. Additionally, a prompt was located directly above the cue, which reminded participants to list as many uses for each object as they could generate. After completing the practice trials, participants immediately began the full norming task, which randomly selected one of the 100 lists of 30 items. These items were presented in a randomized order, and participant responses were self-paced. Following completion of this task, participants were debriefed. The total study took approximately 20 minutes to complete.

**Data Processing**

All responses were initially screened to ensure that participants adhered to the norming task’s instructions. Data from 35 participants were omitted due to excessive blank responses or failure to list object uses (i.e., consistently responding with synonyms or associates), leading to 3121 participants included in the final dataset. The remaining data were then processed in *R* using a procedure that was adapted from Buchanan, De Deyne, & Montefinese’s (2020) guidelines for processing lexical output from feature production tasks. Below, we first detail each step used to create the final dataset before describing the calculation of two affordance measures: Affordance Strength (AFS) and Affordance Set Size (AFFS). Given both the predicted size of the final dataset and because data collection occurred in waves across multiple testing sites, the data processing steps listed below were conducted across several batches of data, ranging from approximately 25 to 500 participants each. For completeness, an *R* script detailing the full cleaning procedure is available at [OSF LINK].

***Cleaning the Raw Data.*** Figure x illustrates the general data cleaning procedure. We began by removing all blank responses along with any responses suggesting that participants were unfamiliar with a specific object (e.g., “I don’t know”, “unknown”, “unsure”, “?”, etc.). Second, because participants generally provided multiple affordances to each cue, each row in the initial dataset generally contained multiple affordances. The *tidytext* package was used to identify and separate individual affordance responses to each cue (De Queiroz et al., 2019). This parsing process assumed that unique affordances were comma-separated, though we additionally corrected for participants who did not follow instructions (e.g., semicolons, periods, spaces, etc.). This resulted in a long-format dataset, with each individual affordance having its own row in the dataset (i.e., “to drink from, throw it, pencil holder” become “to drink from”, “throw it”, and “pencil holder”).

After extracting individual affordances for each object, we next corrected for spelling errors using the *hunspell* package (Ooms, 2022). Because participants were primarily recruited from the United States, the spell check procedure utilized the American English dictionary. For British participants recruited from Prolific, British English spellings were changed to their corresponding American English counterpart (e.g., *colour* and *socialise* become *color* and *socialize*). After using *hunspell* to generate a list of spelling errors, all errors were visually inspected to confirm whether a flagged word was indeed a misspelling or simply a word which was not available in this package’s dictionary. Following the inspection process, all confirmed misspellings were corrected by replacing each misspelled word with its corresponding *hunspell* generated correction.

Once spelling errors were corrected, affordance responses were then tokenized via *tidytext*, which split each affordance phrase into individual words. This step was included to account for two potential issues. First, as noted in the *Procedure*, participants entered their responses into a textbox, which allowed them to list multiple affordances for each cue. However, participants often included extra spacing and tabs in addition to using a comma to separate affordance entries. Thus, the tokenization process removed any additional spacing and punctuation. Second, affordance phrases often contained multiple affordances, in addition to other context specific words (e.g., nouns and adjectives) which may also contain important information regarding object use. By splitting phrases into separate lines in the dataset, we were able to compare base affordances (often represented by verb responses) while also preserving the context in which the affordance occurs. Finally, following the tokenization process, we omitted all stopwords (e.g., *the*, *of*, *but*, etc.), which were dropped via the *stopwords* package (Benoit, Muhr, & Watanabe, 2021).

After tokenizing each affordance and omitting stopwords, the remaining responses were lemmatized and part of speech (POS) tagged. These steps were conducted in *R* with the *udpipe* package (Wijffels, Straka, & Straková, 2023), which uses a trained language model to transform all tokens belonging to a particular set of lexemes (i.e., words with the same common meaning) into a shared lemma (i.e., *swim*, *swam,* and *swimming* become *swim*). We elected to use lemmatization rather than a stemming procedure since, as noted by Buchanan et al. (2020), a word’s stem may not always reflect a word existing within a particular language. Thus, our use of lemmatization ensured that all affordances in the final dataset were words existing in the English language. Finally, the model used for lemmatization was also trained to provide POS tags for wide variety of American English lemmas. However, to ensure accuracy, all tags were manually inspected. For lemmas which could potentially hold more than one tag (i.e., *fish* may be tagged as noun when referring to an animal but as a verb when referencing the lemmatized form of *fishing*), the context in which the original word was produced was used to determine the appropriate tag.

Following the initial cleaning procedure, we inspected the dataset to ensure that all items had been normed by a sufficient number of participants. In doing so, we detected several low frequency cues which did not receive an appropriate number of responses (*n*s < 20). Eighty-five cues met this criterion and were subsequently dropped from the dataset. Additionally, we encountered several cue items that were spelling variations of the same object (e.g., *ax* and *axe*) or singular and plural forms of the same concept (e.g., *noodle* and *noodles*). We combined responses across singular and plural items such that only the singular form was used, so long as changing an object’s plurality did not substantially alter its use. After dropping low frequency cues and correcting for plurals and alternate spellings, the final affordance dataset contained 2825 cues.

After applying the cleaning procedure and dropping low *n* items, the dataset at this stage contained 338949 tokenized items. Because participants were not limited in the number of responses they could provide or in the ways they could format their responses, each response often contained multiple words. However, because affordances reflect actions, we were primarily interested in tokens which were tagged as verbs. As such, we filtered the dataset to remove all adjectives, adverbs, interjections, and uncategorized tokens, which accounted for 5.31% percent of all tokens. Next, nouns were divided into one of two categories: Those which reflected specific object uses (e.g., responding to the cue *bowl* with *hat*, *book* with *doorstop*, etc.) and those which provided contextual information as part of a phrase (i.e., for the cue *meat*, participants might respond *cut with knife*. In this case, only the verb *cut* would be considered an affordance). Non-affordance noun responses were eliminated from the affordance dataset, which removed 97589 tokens. Finally, an additional 16788 verbs were recoded as auxiliary verbs and subsequently excluded from analysis. Commonly, these verbs appeared as part of an action phrase (e.g., for the cue *door*, the response *close to keep you safe*, *close* would be coded as a verb, *keep* would be coded as auxiliary, and *safe* would be coded as a non-affordance noun. Thus, only *close* would be included in the final affordance set). As such, the final affordance dataset contained 202998 tokenized action responses. For completeness, a full dataset containing all participant responses, including contextual nouns, adjectives, and adverbs is available for download on our OSF page.

***Calculating Affordance Measures.*** After removing all non-affordance responses, we computed two affordance measures. First, AFS was calculated by summing each occurrence of a unique affordance received by a particular cue and dividing it by the sum of all affordances that the cue received. In doing so, our process for generating AFS values mirrored that which is used to compute FAS values for free association (e.g., Nelson et al., 2004). For example, if the cue *chair* received a total of 30 responses, with 15 responses being *sit*, 10 responses being *push*, and five responses being *stand on*, the AFS values for *chair* – *sit*, *chair* – *push*, and *chair – stand on* would be .50, .33, and .17, respectively. Thus, higher levels of AFS denote a greater probability that a particular affordance would be listed as a potential action for a cue, suggesting stronger relationship between cue and affordance.

Separately, we calculated AFSS for each cue, which reflect the total number of unique affordance responses for each cue item. Unlike AFS, which provides a measure of affordance probabilities, AFSS provides a quantitative measure of the potential range of action properties which are inherent to a given item. Thus, higher AFSS values reflect a greater number of perceived uses for an object.

**Shiny Application**

While the final dataset is available for download as a .csv file on our OSF page, we have also developed an interactive *R* shiny application, which can be accessed at: https://npm27.shinyapps.io/Affordance\_Norms/. This application provides users with two sets of information. First, the top table displays information regarding each cue word, including mean BOI Rating (Pexman et al., 2019), Concreteness (Brysbaert et al., 2014), SUBLTEX frequency (Brysbaert & New, 2009), age of acquisition (AoA; Kuperman, Stadthagen-Gonzalez, & Brysbaert, 2012), length, AFSS, and the number of participants who responded to each cue. Next, the bottom table displays AFS ratings for all cue – affordance pairs. In addition to providing mean AFS values, we also provide mean forward associative strength values (FAS; Nelson et al., 2004) and cosine similarities (COS; Buchanan et al., 2019a) when available. For both tables, users can search and filter the dataset based on the values in each common, and options are provided for downloading each table as an Excel file or .csv, including any filters which may be applied.

**Results**

**Research Questions**

We now turn to a set of analyses designed to explore the cleaned affordance dataset. First, we provide descriptive statistics for the new AFS and AFSS measures and detail the degree of overlap between the affordance norm set and existing measures of meaning. We then conducted a series of analyses to assess the validity of this dataset. Because our stimuli overlapped with Pexman et al.’s BOI ratings, we assessed the relationship between BOI and AFSS. Specifically, we anticipated that there would be a positive correlation between BOI and AFSS, such that higher BOI ratings would be associated with a larger set of potential object uses. Additionally, we tested for correlations between AFSS and concreteness, age-of-acquisition, and frequency, given that these measures likely also influence a concept’s perceived use. Like BOI, we anticipated a positive correlation between concreteness and set-size, given that higher concreteness would likely result in greater interactivity. However, we anticipated negative correlations with frequency and age-of-acquisition. We reasoned that words which are less common or are acquired later in life would have less uses, given that these words often have referents that are highly specific, which would potentially result in fewer perceived uses (e.g., EXAMPLE).

Finally, given concerns that affordance responses might simply mimic free association norms (i.e., participants were simply responding with the first word that came to mind, regardless of whether it constituted a use), we assessed the relationship between AFS and FAS values taken from Nelson et al. (2004) and COS similarity taken from Buchanan et al. (2019a). These analyses were conducted separately, using small subsets of cue-affordance pairs which overlapped with these existing databases. Because affordances reflect a distinct type of meaning compared to cue-target associations and feature similarity, we anticipated that there would be a weak relationship between AFS and these measures of meaning. However, some overlap was anticipated, given that the measures used to represent various types of meaning may overlap, even though they have been demonstrated to assess different constructs (see Maki & Buchanan, 2008).

**Descriptive Statistics**

[WORDS HERE]

**Validity**

[WORDS HERE]

**Discussion**

[WORDS HERE]

**Conclusion**

[WORDS HERE]

**Open Practices Statement**

Data for all analyses have been made available at [LINK]. The final affordance norm dataset can be accessed at [LINK]. This study was not preregistered.

**Funding Declarations**

[WORDS HERE]

**References**

[FIRST ONE HERE]

Table 1. *Final Sample Sizes for Each Testing Site*

|  |  |
| --- | --- |
| Institution | Total *n* |
| University of Southern Mississippi | 1128 |
| Prolific | 756 |
| University of South Alabama | 365 |
| Midwestern State University | 254 |
| Hope College | 215 |
| University of Connecticut | 152 |
| Central Connecticut State University | 115 |
| Illinois State University | 73 |
| Clemson University | 41 |
| Butler University | 22 |

[TABLE 2]

[FIGURE 1 – DATA PROCESSING PROCEDURE]

**Appendix**

Table A1

[DEMOGRAPHIC INFORMATION]