Affordance Norms for 2825 Concrete Nouns

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Word Count: XXXX

**Author Note**

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 the Open Science Framework: <https://osf.io/68bkt/>. The normed dataset can also be accessed via our interactive Shiny application: <https://npm27.shinyapps.io/Affordance_Norms/>. The authors thank Morgan Ballesteros, Samantha Garcia, and Madisyn Metaxas for their assistance 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), affordance percentage (AFP; i.e., the percentage of participants in our sample who provided a specific 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.

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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. Empirically, 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* when measuring meaning, particularly when assessing the degree to which two words are directly 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 describe 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 measure these types of 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 the increased use of online data collection methods, which have increased the ease of large-scale data collection. 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 of 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. Thus, having multiple measures reflecting separate dimensions of meaning is paramount for understanding how individuals process words. As such, a growing body of research has investigated the links between knowledge acquisition and sensorimotor processing (i.e., embodied cognition; see Barsalou, 1999; Glenberg, 2015; Glenberg & Gallese, 2012; 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; see Barsalou, 2008). Thus, understanding an object’s interactive properties (i.e., its *affordances*; Gibson, 1977) is critical for understanding 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 developed measures quantifying 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 objects receiving higher values were viewed by participants as having a greater degree of perceived interactivity. Consistent with an embodied cognition approach, BOI ratings have been shown to be consistent with existing measures of semantic knowledge, as 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 were combined with three additional ratings of motor dimensionality (graspability, ease of pantomime, and number of actions), the combined ratings explained a greater degree of variance in semantic processing tasks compared to when BOI was used alone. Thus, considered alongside findings from Pexman et al. (2019), it is likely that sensorimotor information plays a critical role when processing a word’s 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 BOI ratings reflect the degree to which individuals can interact with an object, they are highly correlated 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 an object may elicit certain actions is unavailable. While quantifying the degree of interactivity is critical given the proposed connection between sensorimotor experience and knowledge (see Barsalou, Simmons, Barbey, & Wilson, 2003), understanding the various contexts which may facilitate or inhibit potential interactions is equally important. Thus, relying solely upon BOI as a measure of interactivity omits qualitative information which may potentially influence an object’s perceived levels of interactivity.

**The Present Study**

Given the link between sensorimotor experience and knowledge representation, the present study sought to develop a set of affordance norms 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, potential object uses were recorded 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 generated 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 the final set of norms. 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 processed each item (e.g., concreteness, age-of-acquisition, etc.).

**Method**

**Participants**

We recruited 3189 participants from two general settings. First, 2432 undergraduate students were recruited from 9 universities and colleges 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 undergraduate 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. All participants were required to be native English speakers, and Prolific participants were additionally required to have obtained at least a high-school level degree or equivalent.

**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 separate, 30-item lists. Overall, the final set of 3000 words had a mean concreteness rating of 4.61 (*sd* = 0.33; Brysbaert, Warriner, & Kuperman, 2014), a mean SUBTLEX frequency rating of 2.01 (*sd* = 0.87; 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 asked 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 full task instructions can be viewed at https://osf.io/pavjh.

After receiving the instructions, participants first 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 each possible affordances into a textbox which was 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 asked 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 of the task instructions. After completing the five initial practice trials, participants immediately began the full norming task, which randomly presented them with one of the 30-item lists. All items were presented in a randomized order, and participants’ responses were self-paced. Following completion of this task, participants were debriefed. The full 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 3154 participants included in the final dataset. The remaining data were then processed in *R* following a cleaning procedure based on 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 three affordance measures: Affordance Strength (AFS), Affordance Percentage (AFP), and Affordance Set Size (AFFS). Given both the size of the final dataset and because data collection occurred in waves across multiple testing sites, the data processing steps listed below were conducted separately across several batches of data, which ranged from approximately 25 to 500 participants each. For completeness, an *R* script detailing the full cleaning procedure along with a sample dataset is available at [OSF LINK].

***Cleaning the Raw Data.*** 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 (Silge & Robinson, 2016). This parsing process assumed that unique affordances were comma-separated, though we additionally corrected for participants who did not follow instructions (i.e., separating unique uses with semicolons, periods, spaces, etc.). This resulted in a long-format dataset, with each individual affordance having its own row in the dataset (i.e., for the cue cup, the response “to drink from, throw it, pencil holder” would be separated as “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* became *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 typed their responses into a textbox, which allowed them to list multiple affordances for each cue. However, although participants were instructed to separate each response with a comma, they often included extra spacing and tabs in their responses. 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 unique 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, 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 325211 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 initially filtered the dataset to remove all adjectives, adverbs, interjections, and uncategorized tokens, which removed 5.93% percent of all tokens. Next, nouns were divided into two categories: Nouns which reflected a specific object use (e.g., responding to the cue item *bowl* with *hat*, *book* with *doorstop*, etc.) and those which provided contextual information as part of a phrase (i.e., for the cue *bowl*, participants might respond *fill with cereal*. In this case, only the verb *fill* would be considered an affordance). Non-affordance noun responses were eliminated from the affordance dataset, which removed 90303 tokens. Finally, an additional 18642 verbs were recoded as auxiliary verbs and subsequently excluded from analysis. Auxiliary verbs typically appeared as part of an action phrase (e.g., for the cue *door*, a participant might respond *close to keep you safe*. In this example, *close* would be coded as a verb, *keep* would be coded as auxiliary, and *safe* would be coded as a noun reflecting a specific use. Thus, *close* and *safe* would be included in the final affordance set). As such, the affordance measures described below were calculated from 196201 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 the Affordance Measures.*** After removing all non-affordance responses, we computed three 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.

While AFS provides one way of quantifying object-affordance dynamics, we note that due to the open-ended nature of the response task, this value may become skewed when participants consistently respond with multiple affordances per cue, particularly when each participant provides several low probability affordances. To account for this, we separately computed AFP, which reflected the percentage of participants responding to a particular cue with a specific affordance. This was computed by summing the total number of each unique affordance response and dividing it by the total number of participants responding to the cue. To illustrate, if in the previous example, the 30 responses were generated by 15 participants, then while the AFS for *chair-sit* would be .50, the AFP would be 1.00, as each of the 15 participants generated the *sit* as an affordance. As such, AFP values provide an additional measure of affordance strength while correcting for multiple responses.

Finally, 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 has been made 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 report 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 our affordance norms. We begin by providing descriptive statistics for the new AFS, AFP, and AFSS measures before detailing the degree of overlap between the affordance norm set and existing measures of meaning. Next, we report a series of analyses assessing the validity of this dataset. First, because our stimuli fully overlapped with items included in Pexman et al.’s (2019) BOI ratings, we assessed the relationship between BOI and our affordance measures. 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 our affordance measures and concreteness (CON), age-of-acquisition (AoA), 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 fewer total uses, given that these words often have referents that are highly specific, which would potentially result in fewer perceived uses.

Additionally, 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 additionally assessed the relationship between AFS, AFP, and FAS values taken from Nelson et al. (2004) and COS similarity taken from Buchanan et al. (2019a). These analyses were conducted separately, using 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 little overlap between our affordance dataset and these norms, and furthermore, that for any overlapping pairs, only a weak relationship would be detected between affordance measures and other semantic measures. However, some overlap was anticipated, given that the measures used to represent various types of meaning may overlap, even though each type of meaning likely assesses separate constructs (see Maki & Buchanan, 2008).

**Descriptive Statistics**

Table 2 displays descriptive statistics for the AFS, AFP, and AFSS measures of affordances. Overall, the mean AFS value for a given cue-affordance pair was .03 (*SD* = .04). Next, the mean AFP was .07 (*SD* = .09). Importantly, as displayed in Table 2, AFP values provided a greater range compared to AFS, which was largely restricted to weak values. Additionally, each cue item averaged approximately 36 affordance responses (*M* = 35.65, *SD* = 9.12), with set sizes ranging from 12 to 88 items. Finally, an animacy effect emerged, such that words related to living creatures were more likely to have high set-sizes versus nouns denoting non-living things. Thus, living creatures are perceived by participants as conduits for more diverse uses relative to static objects.

**Comparison to BOI and Lexical Variables**

Next, we assessed the relationship between each affordance measure (AFS, AFP, and AFSS) and BOI, concreteness, SUBLTEX frequency, and AoA (Table 3). Because AFS and AFP measures reflect cue-affordance relations (rather than single item properties), the following analysis only assessed AFS and AFP values for each cue’s strongest affordance pairing. Overall, affordance measures were moderately-to-weakly correlated with BOI (*r*s ≤ .33; *p*s ≤ .001), suggesting that our affordance measures were assessing a separate construct relative to BOI. Similarly, AFS and AFP were weakly correlated with concreteness (*r*s ≤ .25; *p*s ≤ .001), though no correlation was detected between AFSS and concreteness (*r* = .01; *p* = .61). AFSS was most strongly correlated with SUBTLEX (*r* = .33; *p* < .001), such that cues with greater frequencies were more likely to have larger sets of uses. Next, AoA was negatively related to both AFSS and AFP (*r*s = -.21; *p*s ≤ .001), suggesting that cues acquired at later ages were more likely to have a reduced range of uses. Finally, regarding our affordance measures, a strong correlation emerged between AFS and AFP (*r* = .81; *p* < .001), which suggested convergent validity between both affordance measures. However, a medium negative correlation was detected between AFS and AFSS (*r* = -.47, *p* < .001), such that as set-size increased, the mean AFS of each cue decreased. However, because our AFP measure controlled for this by assessing affordances at the participant level rather than item-level, the magnitude of this relationship was greatly reduced when affordances were measured via AFP (*r* = -.09; *p* < .001).

**Comparison to Semantic Word Norms**

Finally, we assessed the relationship between AFS and AFP and two other similarity measures: FAS values taken from Nelson et al. (2004), which measure the probability of a word being generated for a given cue via free-association, and COS values derived from Buchanan et al., 2019, which provides a measure of semantic feature overlap between two concepts. We began by computing the percentage of cue-affordance pairs in our dataset which overlapped with each dataset. Because affordances reflect a separate dimension of meaning compared to cue-target association and semantic features, we reasoned that the overlap between datasets would be low, as participants in the present study were instructed to focus specifically on object interactions, rather than its constituent parts or related concepts. Consistent with this notion, overlap between datasets was low, as less than 5% of cue-affordance pairs were available in the associative or semantic datasets (2.86% and 3.35%, respectively). Thus, the lack of overlap between the affordance dataset and existing semantic datasets provides further confidence that our norm set was assessing meaning specifically in terms of object use.

Finally, we assessed the correlations between our affordance measures and FAS and COS for pairs that were shared between each dataset (Tables 4 and 5). Prior to conducting these analyses, we computed subsets of the affordance dataset which only contained pairs that appeared in each dataset. As such, we identified 2702 cue-affordance pairs which were present in the Nelson et al. free association norms and 3163 pairs which were present in the Buchanan et al. (2019a) semantic feature norms. Overall, weak correlations were detected between the two affordance measures and FAS (*r*s ≤ .18; *p*s ≤ .001) and COS (*r*s ≤ .11; *p*s ≤ .001), further suggesting that our affordance norms provide a distinct measure of meaning versus associative and semantic measures.

**Discussion**

The present study sought to expand upon existing measures of word meaning by generating a database of affordance norms for highly concrete nouns. In doing so, we presented participants with a series of object words and had participants list the various ways in which each object could be used. Because our procedure utilized an open-ended, multi-response format, we were able to capture a variety of uses as well as the context in which these actions occurred. [SHINY] Thus, [WHY DOES IT MATTER?]

[RECAP THE EXPERIMENTS]

[LIMITATION – NOT “PRIMING” PARTICIPANTS WITH SPECIFIC TYPES OF OBJECTS (I.E., USING PICTURES) COULD RESULT IN LOWER AFS VALUES, ESPECIALLY FOR “VAGUE” OBJECTS. AREA FOR FUTURE RESEARCH? FUTURE RESEARCH MAY ALSO WISH TO INVESTIGATE INDIVIDUAL DIFFERENCES [REITERATE THAT THIS STUDY IS A STARTING POINT!]

**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]

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

|  |  |
| --- | --- |
| Institution | Total *n* |
| University of Southern Mississippi | 1161 |
| 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. *Descriptive Statistics for Affordance Strength and Affordance Set Size.*

|  |  |  |  |
| --- | --- | --- | --- |
| Measure | *M* (*sd*) | Min. | Max. |
| AFS | .03(.04) | .01 | .61 |
| AFP | .07 (.09) | .01 | 1.00 |
| AFSS | 35.65 (9.12) | 12 | 88 |

Note: AFS = Affordance Strength; AFP = Affordance Percentage; AFSS = Affordance Set Size.

Table 3. *Correlations between Affordance Measures and Lexical/Semantic Variables.*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Measure | AFSS | AFS | AFP | CON | BOI | SUBTLEX |
| AFS | -.47\* | -- |  |  |  |  |
| AFP | -.09\* | .81\* | -- |  |  |  |
| CON | .01 | .13\* | .25\* | -- |  |  |
| BOI | .11\* | .17\* | .33\* | .43\* | -- |  |
| SUBTLEX | .33\* | .09\* | .08\* | .12\* | .23\* | -- |
| AoA | -.21\* | .01 | -.21\* | -.37\* | -.38\* | -.58\* |

*Notes*: AFSS = Affordance Set Size; AFS = Affordance Strength of strongest cue-affordance pair; AFP = Affordance Percentage for highest probability cue-affordance pair; CON = Concreteness (Brysbaert et al., 2014); BOI = Body-Object Interaction (Pexman et al., 2019); SUBTLEX = Frequency (Brysbaert & New, 2009); AoA = Age of Acquisition (Kuperman et al., 2012). \* = *p* < .05.

Table 4. *Correlations between AFS, AFP, and FAS.*

|  |  |  |
| --- | --- | --- |
| Measure | AFS | AFP |
| AFP | .94\* | -- |
| FAS | .18\* | .16\* |

*Notes:* AFS = Affordance Strength; AFP = Affordance Percentage; FAS = Forward Associative Strength derived from Nelson et al. (2004). \* = *p* <.05.

Table 5. *Correlations between AFS, AFP, and COS.*

|  |  |  |
| --- | --- | --- |
| Measure | AFS | AFP |
| AFP | .95\* | -- |
| COS | .11\* | .08\* |

*Notes:* AFS = Affordance Strength; AFP = Affordance Percentage; COS = Cosine Similarity derived from Buchanan et al. (2019a). \* = *p* <.05.