



Affordance norms for 2825 concrete nouns

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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 interactive relations 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., the probability of an item eliciting a particular action response), affordance proportion (AFP; i.e., the proportion of participants who provided a specific action response), and affordance set size (AFSS; i.e., the total number of unique action responses) for each item. Because our stimuli overlapped with Pexman et al.’s, *Behavior Research Methods*, 51, 453–466, (2019) body–object interaction norms (BOI), we tested whether AFS, AFP, and AFSS were 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 AFP and two separate measures of relatedness: cosine similarity (Buchanan et al., *Behavior Research Methods*, 51, 1849–1863, 2019a, *Behavior Research Methods*, 51, 1878–1888, 2019b) and forward associative strength (Nelson et al., *Behavior Research Methods, Instruments, & Computers*, 36(3), 402–407, 2004). All analyses, however, revealed weak relationships between affordance measures and existing semantic norms, suggesting that affordance properties reflect a separate construct.

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. 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 assessing similarity, particularly when evaluating 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

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Nelson et al., 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 (e.g., *mouse* and *house* rhyme). Thus, while semantic features describe meaning primarily in terms of similarity, associations place a greater emphasis on the context in which words are used.

Given the focus on semantic and associative descriptions of meaning, 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 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 et al., 2019a; McRae et al., 2005; associated concepts; De Deyne et al., 2019; Nelson et al., 2004). The past two decades have yielded several 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 facilitated 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 et al., 2019b).

While semantic and associative norms are important proxies for assessing meaning and relatedness between concepts, 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. Indeed, a growing body of research has investigated the links between knowledge acquisition and sensorimotor processing (i.e., embodied cognition; for reviews see Barsalou, 1999; Glenberg, 2015; Glenberg & Gallese, 2012). Because sensorimotor systems are active whenever individuals interact with 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, how individuals can potentially engage with objects in their environment (i.e., the object's *affordances*; Gibson, 1977; see Wagman, 2020) reflects a critical component of meaning. Unlike semantic and associative-based measures, affordances reflect potential interactive relations existing between actors and objects. As such, affordances may reflect a variety of common and less common actions (e.g., a chair affords sitting but also standing on to reach an object) and are thought to be perceived automatically (Tucker & Ellis, 1998; see also Azaad et al., 2019). However, existing feature production and free association norms

do not capture a range of object uses, as these norms instead emphasize an object's constituent parts and related concepts, respectively, rather than focusing on its inherent, actionable properties.

Given the role of sensorimotor processes in knowledge acquisition, previous work has sought to develop norms measuring various aspects of sensorimotor experience, including the degree of strength to which an experience is perceived and the primary sensory modality by which it occurs (e.g., the Lancaster Sensorimotor Norms; Lynott et al., 2020), an object's degree of manipulability (e.g., graspability and functional usage; Salmon et al., 2010), and importantly, body-object interactivity (BOI; e.g., Muraki et al., 2022; Pexman et al., 2019; Tillotson et al., 2008), which quantifies 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 capture aspects of semantic knowledge. For example, BOI is a strong predictor of responses in semantic decision tasks and has been found to facilitate lexical decision responses derived from the English Lexicon Project (Balota et al., 2007) and responses from the Calgary Semantic Decision Project (Pexman et al., 2017). Importantly, for lexical and semantic decision tasks, any benefits of BOI on responses 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. Additionally, Heard et al. (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 than when BOI was used alone. Thus, considered alongside findings from Pexman et al. (2019), sensorimotor information appears to play 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 three potential shortcomings which may limit their broader use. First, BOI ratings are highly correlated with concreteness, given that by nature they reflect the degree to which individuals can interact with an object. Consistent with this, Pexman et al. (2019) reported that performance on lexical tasks improved 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. 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 et al., 2003), understanding the various contexts which may facilitate or inhibit potential interactions is equally important. Finally, having participants rate an object's general levels of interactivity may simply be too vague of a measure, as when individuals encounter an object, they generally have a specific use in mind which may facilitate or inhibit interactivity depending on specific environmental factors. Thus, relying solely upon BOI as a measure of interactivity omits important qualitative information which may influence an object's perceived level 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 participants to freely report affordances without experimenter-provided cues or prompts. As described below, participants responded to a series of lexical cues, and object use was framed in terms of affordances, such that participants were instructed to list the specific ways a given object could potentially be used or interacted with. Potential object uses were recorded using a method akin to feature production and free association tasks (cf. McRae et al., 2005; Nelson et al., 2004). By not providing participants with pictures of each object or prompting participants with specific types of objects, we were able to reduce the likelihood of biasing participants towards responding with specific uses. This allowed us to capture a range of responses, which maximized the potential number of affordances that could be generated for each object.

In the following sections, we detail the creation of the affordance norm dataset, including how our final sample size was determined, exclusion criteria, and all manipulations and measures. We then describe an interactive web portal designed to facilitate exploration of the final norm set. Finally, we discuss a series of analyses which compared the affordance measures generated from this dataset with two existing measures of meaning—forward association strength (FAS) values derived from Nelson et al.'s (2004) free association norms, and cosine similarity (COS) taken from Buchanan et al.'s (2019a) feature production norms), BOI ratings (Pexman et al., 2019), animacy (VanArsdell & Blunt, 2022), and several lexical variables which could potentially influence how participants processed each item (e.g., concreteness, age of acquisition, cue set size, etc.).

Method

Participants

We recruited 3189 participants from two general settings. First, 2432 undergraduate students were recruited from nine universities and colleges located within the northeastern, midwestern, and southern United States and completed the study in exchange for partial course credit. The remaining 757 participants were recruited via Prolific (www.Prolific.co) and were compensated at a rate of \$3.00 per 20-minute session. We initially targeted 3000 participants, which ensured that each object would be presented to at least 30 participants. However, data collection was extended as funding permitted. Table 1 displays the final numbers and sample characteristics for each testing site following data cleaning. All participants completed the experiment online. To be eligible, 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 Medical Research Council (MRC) psycholinguistic database (Coltheart, 1981). Words were selected based on concreteness, such that only high-concreteness words were included (M concreteness ≥ 4.25). Of the 3005 words we generated, five were randomly selected to serve as practice items. The remaining 3000 items were once randomized

Table 1 Final sample sizes and sample characteristics for each testing site

Institution	Total n	M (SD)	Age	% Female
University of Southern Mississippi	1161	21.00 (5.86)		83.84
Prolific (United Kingdom)	575	37.89 (12.13)		48.21
University of South Alabama	365	19.56 (3.92)		75.34
Midwestern State University	254	19.50 (2.77)		75.59
Hope College	215	18.59 (0.80)		73.95
Prolific (United States and Canada)	181	37.66 (11.62)		46.75
University of Connecticut	152	18.69 (1.01)		73.68
Central Connecticut State University	115	20.54 (4.89)		60.00
Illinois State University	73	19.22 (1.85)		84.93
Clemson University	41	21.37 (5.66)		80.49
Butler University	22	20.63 (2.50)		68.18

Note: For completeness, Prolific participants are split by country of origin

before being equally split into 100 separate, 30-item lists. Overall, the final set of 3000 cue words had a mean concreteness rating of 4.61 ($SD=0.33$; Brysbaert et al., 2014), a mean SUBTLEX frequency rating of 2.01 ($SD=0.87$; Brysbaert & New, 2009), a mean BOI rating of 5.18 ($SD=0.60$; Pexman et al., 2019), and a mean animacy rating of 342.63 ($SD=242.74$) based on VanArsdall and Blunt's (2022) living scale.

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 view a series of object words and would be asked to list as many uses for each object (i.e., affordances) 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 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 generate as many affordances as they reasonably could in response to the cue. Participants typed each affordance response into a textbox which was located directly below the cue. 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 object use 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 being included in the final dataset. The remaining data were then processed in R following a cleaning procedure based on Buchanan et al. (2020) guidelines for processing lexical output from feature–production tasks. Below, we detail each step used to create the final dataset before describing the calculation of three affordance measures: affordance strength (AFS), affordance proportion (AFP), and affordance set size (AFSS). Given 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 on our OSF page.

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 via 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 responses flagged as errors were visually inspected to confirm whether the word was indeed a misspelling or simply a word which was not available in this package's dictionary. Following the inspection process, 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 section, 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, the affordance phrases isolated in the previous step often contained multiple actions, as well as other context-specific words (e.g., nouns and adjectives) which may also contain important information regarding object use. As such, these phrases were further split into separate lines, particularly when they contained a mix of nouns and verbs (i.e., for the cue *cup*, the affordance phrase “pencil holder” would be separated as “pencil” and “hold”). By separating affordance phrases, we were able to compare unique affordances (typically represented by verb responses; e.g., “hold”) while also preserving the context in which the affordance occurred (“pencil”). Finally, following the tokenization process, we omitted all stopwords (e.g., *the*, *of*, *but*, etc.), which were dropped via the *stopwords* package (Benoit et al., 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 a 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 a 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 received responses from a sufficient number of participants. In doing so, we detected several low-frequency cues which did not receive an appropriate number of responses ($ns < 20$). Eighty-five cues met this criterion and were 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-response items, the dataset at this stage contained 325,211 unique 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 90,303 tokens. Finally, an additional 18,642 verbs were recoded as auxiliary verbs and subsequently excluded from the analysis. Auxiliary verbs typically appeared as part of an action phrase. For example, when responding to 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 196,201 tokenized action responses, and each cue received responses from at least 24 participants. 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, for each cue–affordance pair, we computed AFS as the frequency of each unique affordance divided by the summed frequency of all affordances that the cue received. In doing so, our process for generating AFS values mirrored how FAS values are computed as measures of 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 corresponding AFS values for *chair–sit*, *chair–push*, and *chair–stand on* would be .50, .33, and .17, respectively. Thus, AFS reflects the probability that a specific affordance would be generated in response to a cue, with higher AFS values denoting a stronger cue–affordance relation.

While AFS provides one method of quantifying object–affordance dynamics (related to the concept of *canonical affordances*; see Costall, 2012), we note that due to the open-ended nature of our response task, AFS is likely to become negatively skewed when each participant provides multiple responses to a single cue, particularly when responses are a series of low probability affordances. To account for this, we separately computed AFP, which reflects the proportion of participants who responded to the cue with a specific affordance, rather than the frequency with which an action was listed relative to other affordances (i.e., AFS). To compute this measure, we again began by computing the frequency of each unique affordance response. However, instead of dividing by the total number of affordances, we instead divided by the number of participants who responded to the cue. Based on the previous example, if all 15 participants *responded* to chair with *sit*, then the AFP for this pair would be 1.00, even though the AFS value would equal 0.50. Thus, AFP values provide an additional measure of affordance strength while also correcting for limited AFS range due to multiple cue responses per participant.

Finally, we calculated AFSS for each cue, which reflects the total number of unique affordance responses for each cue item. In the example from above $AFSS = 3$ because *chair* received three unique responses (*sit*, *push*, *stand*). Unlike AFS and AFP, which each measure the probability of objects eliciting specific actions, 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://nrm27.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 et al., 2012), length, cue set size (QSS; Nelson et al., 2004), AFSS, animacy (VanArsdall & Blunt, 2022), and the number of participants who responded to each cue. Next, the bottom table displays AFS and AFP ratings for all cue–affordance pairs. In addition to providing these values, this table also reports 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 overlapping items and semantic/lexical values, and options are provided

for downloading each table as an Excel file or .csv, including any filters which may have been 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 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, AoA, SUBLTEX frequency, and QSS, 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. We additionally anticipated a positive relationship between QSS and AFSS, as cues with a greater number of associates would likely reflect broader concepts and, as a result, lend themselves to more uses. Similarly, we anticipated a positive correlation between animacy and AFSS, as animate cues (e.g., people or animals) are likely to engage in their own actions, which may change how individuals interact with them. Finally, we also expected negative correlations between AFSS and AFS. However, because AFP was designed to mitigate the effects of set size on affordance strength, this negative effect was expected to be greatly reduced when assessing the relationship between AFSS and AFP. Finally, we additionally 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.

Finally, given potential 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 slightly higher set sizes versus nouns denoting non-living things (37.94 vs. 35.40; $t(743) = 3.73$, $SEM = .68$, $p < .001$, $d = 0.27$). Thus, living creatures were 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, SUBTLEX frequency, AoA, and QSS (Table 3). Because the 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 (i.e., the cue–affordance pair with the highest AFS or AFP value between cue and affordance). Overall, affordance measures were weakly to moderately correlated with BOI ($r_s \leq .33$; $p_s \leq .001$), suggesting that our affordance measures were assessing a separate construct with only partial overlap with BOI. Similarly, AFS and AFP were weakly correlated with concreteness ($r_s \geq .13$, $p_s \leq .001$, and no correlation was detected between AFSS and concreteness, $r = .01$; $p = .611$). 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 ($r_s = -.21$; $p_s \leq .001$), suggesting that cues acquired at later ages were more likely to have a reduced range of uses. Additionally, QSS was weakly correlated with AFSS ($r = .13$, $p < .001$), suggesting that cues with more associative neighbors were additionally more likely to have larger sets of potential actions. However, a weak negative correlation emerged between QSS and AFS ($r = -.09$, $p < .001$). Finally, animacy was also positively correlated with AFSS ($r = .14$, $p < .001$) and negatively correlated with both AFS and AFP ($r_s \geq -.30$; $p_s \leq .001$). Thus, increased set sizes for animate objects were related to an overall decrease in AFS and AFP.

Table 2 Descriptive statistics for affordance strength and affordance set size

Measure	<i>M</i> (<i>sd</i>)	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 proportion; AFSS = affordance set size

Table 3 Correlations between affordance measures and lexical/semantic variables

Measure	AFSS	AFS	AFP	CON	BOI	SUBTLEX	AoA	Animacy
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*	--	
Animacy	.14*	-.30*	-.31*	-.34*	-.37*	.01	.05	--
QSS	.13*	-.09*	-.03	-.04	.02	.22*	-.10*	.02

Notes: AFSS = affordance set size; AFS = affordance strength of strongest cue–affordance pair; AFP = affordance proportion 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); animacy = living scale ratings derived from VanArsdall and Blunt (2022); QSS = cue set size (Nelson et al., 2004); * $p < .05$

Regarding our affordance measures, a strong correlation emerged between AFS and AFP ($r = .81$; $p < .001$), which indicated strong convergent validity between the two affordance measures. However, a medium negative correlation was detected between AFS and AFSS ($r = -.47$, $p < .001$), such that as the set size increased, the mean AFS of each cue decreased. Because our AFP measure controlled for this by assessing affordances at the participant level rather than the item level, the magnitude of this relationship was greatly reduced when affordances were measured via AFP ($r = -.09$; $p < .001$). Thus, compared to AFS, AFP was less biased by cues having large set sizes.

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. (2019a), 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 from that of 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 features 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 evidence 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

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). * $p < .05$

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 ($r \leq .18$; $ps \leq .001$ and COS ($r \leq .11$; $ps \leq .001$), further suggesting that our affordance norms provide a distinct measure of meaning versus associative and semantic measures.

General discussion

The present study sought to expand upon existing measures of word meaning by generating a set of affordance norms for highly concrete nouns. Unlike existing semantic word norms, which operationalize meaning in terms of shared features or free associations, affordances ascribe meaning based on an object's actionable properties (Gibson, 1977). Thus, affordances describe complex actor–object interactions, which are less likely to be captured by semantic feature production or free-association tasks. To generate these norms, we presented participants with a series of object words and had participants complete an open-ended response task in which they listed the various ways in which each object could be used. In doing so, we were able to capture a variety of affordance information for each object, including common/uncommon affordances (represented by AFS and AFP) and set sizes for each object (AFSS). Finally, we developed an interactive R Shiny application, which provides easy access to the final dataset and contains several options for exploring these norms.

To test the validity of our affordance norms, we began by comparing our three affordance measures with several lexical/semantic variables, including BOI, concreteness, SUBTLEX frequency, and AoA. Because BOI ratings capture information regarding an object's perceived interactivity, we anticipated that affordance measures would correlate with BOI. However, mostly weak correlations emerged between BOI and affordances, suggesting that each measure likely assesses separate constructs. Additionally, all affordance measures were moderately correlated with concreteness, although we note that given the restricted range of this value (i.e., all cues were highly concrete nouns), caution is needed when interpreting affordance–concreteness relations. Finally, an animacy effect was detected, such that animate

objects had greater set sizes, though negative correlations between animacy and AFS/AFP suggested that these greater set sizes likely reduced the overall strength of each affordance. However, given that only 745 of our cues appeared in VanArsdall and Blunt's (2022) animacy norms, more work will be needed to fully explore the link between animacy and affordances.

Separately, a weak positive correlation was detected between AFS and SUBTLEX, while a weak negative correlation emerged between AFSS and AoA. The presence of these correlations suggests two important insights. First, higher-frequency cues generally lend themselves to a greater number of uses, likely because high-frequency nouns often provide more general depictions of objects, rather than being highly specific. Second, cue objects that are acquired later in life are likely to have more limited use sets, as these items tend to be less frequently occurring and lend themselves to a more specific set of uses. Additionally, our finding that frequency correlates with AFS is consistent with a behavioral ecology account of affordances, as objects which occur more frequently in one's environment are more likely to lend themselves to multiple uses (i.e., objects occurring more frequently in one's environment provide more opportunities for interaction; see Withagen et al., 2012, for review). Finally, our finding that QSS is positively related to affordance set size but negatively related to AFS is consistent with our prediction that affordances with larger overall set sizes would have weaker overall cue–affordance relations.

In addition to assessing the relationships between our three affordance measures and lexical/semantic variables, we also tested for correlations between any of the affordance measures. Overall, we found a strong negative correlation between AFS and AFSS, which likely occurred since each cue generally had a small number of relatively common affordances (i.e., affordances produced by most participants) while simultaneously having a relatively large number of uncommon affordances that were only generated by a few individuals (i.e., plotting the frequency of each affordance produces a long-tailed distribution). As a result, this increased each cue's AFSS, and because AFS was computed by dividing the sum of each unique affordance by the total number of affordances that were produced, this lowered the overall AFS for each cue–affordance pair. To account for this, we computed AFP as an additional affordance measure, which reflects the proportion of participants who responded with a specific affordance, rather than as an item-level proportion as is computed with AFS. Overall, AFS and AFP were strongly positively correlated, providing evidence of convergent validity. Importantly, although AFP was negatively correlated with AFSS, the magnitude of this correlation was greatly reduced relative to AFS ($-.09$ vs. $-.47$, respectively). Thus, AFP likely captured the same information as AFS, without being biased by AFSS.

Next, we tested the degree of overlap between our two cue–affordance measures (AFS and AFP) and semantic/associative measures. First, we assessed the degree to which cue–affordance pairs overlapped with cue–target pairs in the Nelson et al. (2004) free-association norms and Buchanan et al.'s (2019a) semantic feature production norms. For both datasets, overlap was low, with less than 5% of pairs appearing in both the affordance norms and either the free association or feature production norms. The lack of overlapping pairs suggests that responses in our affordance norming task were successfully reflecting actionable properties, rather than related associates or features of cue items. To confirm this, we assessed the correlations between AFS, AFP, FAS, and COS. Consistent with our predictions, affordance measures were weakly correlated with associative/semantic measures of meaning, demonstrating divergent validity.

Overall, our affordance norms provide a useful starting point for investigating common versus uncommon affordances, which future research can leverage to further investigate the links between object perception, object use, and creativity. For example, recent work by Matheson and colleagues (e.g., Matheson et al., 2017; Matheson & Kenett, 2020, 2021) has explored creativity using the Alternative Uses Task (AUT) in which, like our affordance norming task, participants are provided with a cue word (generally a concrete noun) and generate a list possible uses. However, unlike the present study in which participants received no guidance on the types of affordances they should generate, participants completing an AUT are often encouraged to be creative when generating potential uses. Given the similarities between our norming task and the AUT, our affordance norms may be particularly useful for researchers investigating creativity via generation tasks like the AUT.

Additionally, our affordance norms may be particularly useful for investigating the connection between perceived use and semantic processing. For example, Surber et al. (2023) recently demonstrated that object priming is facilitated by both semantic and affordance primes, suggesting that semantic and affordance properties are similarly processed. However, given the low degree of overlap between our affordance measures and semantic norms, it is likely that affordances denote a type of meaning separate from semantic features. Moreover, previous research suggests that various associative/semantic measures likely assess different domains of meaning, such that specific types of meaning may operate separately from others (e.g., Maki & Buchanan, 2008; Patterson & Ralph, 2016). Based on this account, action-specific knowledge would constitute a separate type of meaning from associations and semantic features, although some overlap would be expected between measures, given that based on affordance theory, an object's most salient features drive its perceived uses (Gibson, 1977; Tucker & Ellis, 1998; see Wagman, 2020, for review).

However, given the limited number of cue–affordance pairs overlapping between our affordance norms and other semantic/associative norm sets, more work is needed to fully understand the degree to which affordances carry unique information that is separate from other measures of meaning.

While the present study is the first to utilize an open-ended approach to measuring object interactions, we note that Pexman et al. (2019) provided some quantification of object interactivity. As such, the low correlations between affordance measures and BOI are somewhat surprising, given that both datasets measure perceived interactivity. However, we note that differences in response format between the two studies may partially explain this discrepancy. Unlike the present study which utilized an open-ended response format, Pexman et al. had participants rate each object's perceived interactivity via a Likert scale, rather than having them list specific potential uses. However, the increased response variability due to our open-ended response format may have limited potential correlations between affordances and BOI. Additionally, although Likert scale ratings provide useful information regarding the strength of potential interactivity, this response format cannot reveal information regarding the specific affordances being activated when participants rate their interactions. Therefore, an additional benefit of our open response format was that it provided additional context regarding potential object interactivity. Thus, the present study complements existing measures of interactivity while also attempting to qualitatively investigate the degree to which specific affordances are linked to specific cues.

Although our open response format was designed to capture a greater variability in responses, we note that this general design is also consistent with previous associative/semantic norming studies which have similarly allowed participants to make multiple responses to a single cue (e.g., De Deyne et al., 2019). Furthermore, like previous studies, participants provided their responses after reading each cue word. We elected to use this approach, rather than presenting participants with pictures of objects, as we wanted to avoid inadvertently biasing participants towards responding with specific affordances based on viewing a certain type of object. However, this may have inflated AFSS values, particularly for objects which may have been vague or objects which participants may have been unfamiliar with. Thus, follow-up studies may consider having participants respond to picture cues rather than lexical cues. Additionally, individual differences in how participants interact with their environment may also influence the probability of specific affordances being elicited. As such, future studies may wish to explore the effects of height, age, and disability status on affordances.

Finally, while the present study provides an important starting point for investigating cue–affordance relations,

a complete understanding of how individuals process an object's affordances also requires knowledge of which objects are most likely to be used to achieve a desired goal or action. As such, future studies may wish to answer this question by presenting participants with a list of affordances and having them respond with the specific objects that could be used to successfully accomplish the action. Additionally, because semantic variables are often associated with the speed of lexical access in visual word recognition studies, future research may also wish to assess the degree to which affordance variables account for variance within this paradigm after accounting for other lexical/semantic variables. Ultimately, however, the present study provides an important starting point for measuring the link between affordances and action.

Conclusion

Previous studies have commonly assessed meaning in terms of semantic features or cue–target associations. In the current study, we present the first set of affordance norms along with a corresponding R Shiny application, which provides researchers with two measures of perceived object use (AFS and AFP) and AFSS values. Importantly, we utilized an open-ended response format when developing this norm set, which allowed us to capture a wide range of potential object uses. Overall, we demonstrate that affordance properties are independent from other semantic measures (e.g., FAS and COS) while also showing weak correlations with BOI values, which quantify object interactivity. As such, affordance information appears to reflect a construct that is separate from other measures of meaning, though more work is needed to fully explore the relationship between affordances and other semantic measures.

Author note 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.

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Availability of data and materials A .csv file containing the final affordance norm dataset can be directly accessed at <https://osf.io/jb45e>. Additionally, the final dataset can be accessed via our interactive Shiny application: https://npm27.shinyapps.io/Affordance_Norms/.

Code availability Data and R code for all analyses have been made available at <https://osf.io/68bkt/>.

Declarations All participants provided informed consent prior to their participation.

Conflicts of interest The authors declare no conflicts of interest.

Ethics approval The materials and procedures for this study were approved by the Institutional Review Boards at The University of Southern Mississippi (#IRB-20-318) and Midwestern State University (#22092201).

Consent to participate Prior to completing the study, all participants provided their consent to participate and have their data published.

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