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ORIGINAL ARTICLE

Heterogenous abstract concepts: is "ponder" different from "dissolve"?

Emiko J. Muraki[1] · David M. Sidhu[1] · Penny M. Pexman[1]

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Abstract

Abstract words have usually been treated as a homogenous group, with limited investigation of the influence of different underlying representational systems for these words. In the present study we examined lexical–semantic processing of abstract verbs, separating them into mental state, emotional state and nonembodied state types. We used a syntactic classification task and a memory task to investigate behavioural differences amongst the abstract verb types. Semantic richness effects of each of the verbs' associates were then investigated to determine the relationship of linguistic associations to semantic processing response times for abstract verbs. We found a modest effect of abstract verb type, with mental state abstract verbs processed more quickly than nonembodied abstract verbs in the syntactic classification task; however, this effect was task dependent. We also found that memory was less accurate for the mental state abstract verbs. The semantic richness analysis of abstract verb associates revealed (1) that the concreteness of an abstract verb's associates has a positive relationship to the verb's response time and (2) a negative relationship between response time and age of acquisition for associates of nonembodied verbs. The results provide support for the proposal that abstract concepts engage complex representations in modal and linguistic systems.

Introduction

Theories of word meaning representation tend to fall into two main categories: amodal theories based on symbolic mental representations (Leshinskaya & Caramazza, 2016; Mahon, 2015; Pylyshyn, 1980) and theories that propose word meaning is grounded in multimodal representations, wherein simulations of perceptual, motor and introspective states are activated when we process a word or concept, regardless of the presence of actual sensory-perceptual input (Barsalou, Santos, Simmons, & Wilson, 2008; Borghi, Barca, Binkofski, Castelfranchi, Pezzulo, & Tummolini, 2019; Glenberg, 2015; Lakoff & Johnson, 1999). Evidence in support of grounded theories of semantic representation has largely come from work on concrete concepts, which are words with a physical or tangible referent. For example, neuroimaging studies have shown that when participants read concrete action verbs relating to specific body areas (e.g. kick, lick, etc.), there is activation in the corresponding somatotopic regions of the motor and premotor cortex (Hauk, Johnsrude, & Pulvermuller, 2004). This involvement of the motor system in concrete and action word processing has now been demonstrated in numerous studies (Aziz-Zadeh, Wilson, Rizzolatti, & Iacoboni, 2006; Desai, Binder, Conant, & Seidenberg, 2010; Kemmerer, Castillo, Talavage, Patterson, & Wiley, 2008).

Abstract words, in contrast, represent noun, verb and other concepts that are not easily connected to a tangible referent or action. The meanings of abstract words tend to be influenced by individual life experiences and culture, as compared to the meanings of concrete words for which there are clear physical referents (Barsalou, 1987). Explaining how abstract word meaning is represented has consistently been raised as a challenge for grounded theories of semantic representation, by proponents of both grounded and amodal theories (Barsalou, 2016; Borghi, Binkofski, Castelfranchi, Ciamatti, Scorolli, & Tummolini, 2017; Dove, 2016; Mahon & Caramazza, 2008; Meteyard, Cuadrado, Bahrami, & Vigliocco, 2012).

Abstract word representation has primarily been investigated in terms of how it differs from concrete word representation. Representational differences between concrete and abstract concepts have been demonstrated through what is known as the "concreteness effect" wherein concrete words are processed more quickly than abstract words in a variety of linguistic tasks (James, 1975; Kounios & Holcomb,

✉ Emiko J. Muraki
ejmuraki@ucalgary.ca

[1] University of Calgary, Calgary, Canada

1994). Despite frequent recognition that abstract concepts remain difficult to account for within grounded cognition theories of semantic representation, limited progress has been made to substantiate theoretical accounts for representation of abstract concepts specifically.

Theories of abstract concept representation

The Affective Embodiment Account (AEA) suggests that affective experience and emotional development are more critical to the underlying representation of abstract concepts than they are to the representation of concrete concepts (Borghi et al., 2017; Kousta et al., 2011). This position is supported by the results of Kousta et al. who found an abstractness effect (facilitated processing of abstract words vs. concrete words; a reversal of the traditional concreteness effect) when controlling for imageability and context availability in a lexical decision task (LDT). That facilitory effect of abstractness was ultimately attributed to differences in valence (the degree to which a word is positive or negative in nature) between abstract and concrete words. That is, abstract concepts tend to be more valenced than concrete concepts, and LDT responses tend to be faster for valenced than for neutral words (Siakaluk et al., 2016). Indeed, fMRI studies have demonstrated that abstract concepts activate the rostral anterior cingulate cortex, which is known to have a regulatory role in emotion processing (Vigliocco et al., 2014). This raises the question of whether emotion concepts are truly a subset of abstract concepts or whether they belong to their own discrete category of concepts, separate from abstract and concrete (Altarriba & Bauer, 2004). A grounded cognition perspective can, however, readily account for the differences between emotional abstract concepts and other abstract concepts, since emotions are a bodily experience that would provide a distinct grounding mechanism for these types of abstract words.

Some of the most promising accounts of abstract word representation are multiple representation theories, which propose that abstract concepts are grounded in perception, action and emotion as well as in linguistic information. For example, according to the language and situated simulation view (LASS; Barsalou, 2008), the linguistic and simulation systems operate in parallel during semantic processing. Concepts, either concrete or abstract, activate combinations of linguistic and simulated information in different brain areas depending on their meaning. Similarly, the Words as Social Tools proposal (WAST; Borghi & Binkofski, 2014; Borghi et al., 2019) asserts that concept representation develops from both perceptual/motor and linguistic experience. The WAST view places greater importance on the social dimension of word acquisition and how the social experience of language contributes to its representation. Both of these theories take into account the fact that abstract words have diverse referents, both within an individual's personal experience and between different individuals. The diversity of referents leads to complex representations underpinning abstract concepts, demonstrated by more distributed neural activation when processing the meanings of these words (Pexman, Hargreaves, Edwards, Henry, & Goodyear, 2007).

Multiple representation theories provide the opportunity to consider that different kinds of abstract concepts may rely on different underlying representational systems. Thus, the expectation would be that emotional abstract concepts may be grounded in emotional experience, while mental state or introspective abstract concepts may be grounded in internal states and that the most abstract concepts may rely more heavily on linguistic information (Dove, Barca, Tummolini & Borghi, 2020). However, a paucity of research on behavioural differences amongst discrete types of abstract words makes it difficult to evaluate such hypotheses.

Investigations of abstract word representation

Thus far, investigations of abstract word representation have largely focused on three lines of inquiry: identifying properties and features that are generated for abstract words, identifying clusters of abstract concepts based on similar semantic information, and investigating semantic richness effects in abstract word processing.

Property generation tasks have been used to compare the properties or characteristics associated with abstract and concrete words. In these studies, participants are asked to generate the properties of a cue word. Properties generated for abstract words tend to reflect social, event and introspective aspects of situations, whereas concrete words evoke entities, objects, buildings, locations, etc. (Barsalou & Wiemer-Hastings, 2005; Wiemer-Hastings & Xu, 2005). Similar inferences were drawn from a study by Zdrazilova, Sidhu and Pexman (2018), which took a slightly different approach involving a "Taboo task" where each participant tried to have a study partner guess a target word without using the word itself in their description. Participants tended to use more references to people and introspections when trying to describe abstract nouns and more references to objects and entities when trying to describe concrete nouns. Overall, these findings suggest that abstract concepts are to some degree grounded in social experience, as predicted by the LASS and, to a greater extent, WAST proposals.

Other research has focused on identifying clusters of abstract concepts. The rationale is that similarities in semantic information between abstract words may be indicative of shared underlying representational structures, which can then be tested against those proposed by multiple representation theories. Troche, Crutch and Reilly (2014) investigated the organization of abstract and concrete English nouns and identified three latent semantic factors: affective association/social cognition, perceptual salience and magnitude. Similarly, Harpaintner, Trumpp and Kiefer (2018) identified three distinct clusters of properties for abstract concepts that were characterized by; (1) a high proportion of sensorimotor features, (2) a high proportion of internal/emotional features and (3) a high proportion of verbal association features. Harpaintner, Trumpp, & Kiefer (2020) have also demonstrated that abstract concepts with motor and visual properties are grounded in modal brain areas in related ERP effects. Villani, Lugli, Liuzza, and Borghi (2019) identified four clusters of abstract concepts: physical, spatio-temporal and quantitative concepts, self- and sociality concepts, philosophical/spiritual concepts and emotional/inner state concepts. There is considerable overlap between the clusters identified in these three studies, with the exception that only Harpainter et al. found a clear verbal association cluster that would indicate some reliance on linguistic representations for abstract concepts. Nonetheless, such findings are consistent with some of the modalities proposed to underlie word meaning in hybrid theories such as LASS and WAST.

The other line of inquiry used to address abstract concept representation has been to examine semantic richness effects in abstract language processing. Semantic richness effects involve the tendency for words that are high in a variety of semantic dimensions to be processed more quickly in lexical and semantic tasks: greater semantic richness facilitates processing (Pexman, 2012). This area of study has identified semantic richness effects in abstract language related to the number of semantic neighbours (Recchia & Jones, 2012) and also verb-specific effects of age of acquisition, valence, arousal and relative embodiment (the degree to which a verb's meaning involves the human body; Sidhu, Heard & Pexman, 2016; Sidhu, Kwan, Pexman & Siakaluk, 2014). Taken together, these results further support the proposal that abstract concepts are represented through multiple dimensions such as embodiment (in the case of verbs specifically), emotional valence, arousal and the degree of relationships to other words.

Further, semantic richness effects in abstract language processing have been demonstrated to be task-dependent. Zdrazilova and Pexman (2013) found that the same set of abstract word stimuli elicited different semantic richness effects in an LDT compared to a semantic decision task (SDT). In LDT, an effect of context availability was observed (words with more contextual information exhibited faster response times), while in SDT the effects of sensory experience and emotional valence were observed. This task dependency is well explained by multiple representation theories, in that representational mechanisms can vary not only as a function of semantic content, but also as a function of task or context demands. In this case, linguistic representation may facilitate shallow processing employed in LDT, but the deeper processing of word meaning required by the SDT engages more sensory and emotional representations.

A final, often overlooked opportunity to investigate abstract word representation is the contribution of their associative networks. The number of associates generated for a word in free association has been studied as a dimension that contributes to overall semantic richness (Buchanan, Westbury, & Burgess, 2001; Dunabeitia, Aviles, & Carreiras, 2008; Locker, Simpson, & Yates, 2003). It has been argued, however, that these associations matter more for abstract words than for concrete words. For instance, Barsalou and Wiemer-Hastings, (2005) proposed that abstract words activate associates when processed in isolation, because situational or contextual information is less available than it is for concrete words. They described a study comparing the information generated when abstract and concrete words are presented in isolation under three different task conditions: with instructions to either generate associates for each word, to construct and describe images for each word and finally to produce properties for each word. The researchers found that participants in the properties condition tended to produce information similar to that of the word association condition for abstract words and information similar to that of the imagery condition for concrete words. This would suggest that the underlying representations of abstract words involve greater reliance on associative structures. However, it is not clear to what degree these associates contribute to abstract word representation, if they provide only surface-level, lexical information (as proposed by Barsalou & Wiemer-Hastings, 2005) or whether semantic content of the associate itself contributes in some way to representation of the abstract word.

The previous research using property generation tasks, ratings tasks, and cluster-based analysis has begun to map the semantic space of abstract words; however, few works have examined how these clusters of semantic similarity may translate into behavioural effects. Even less number of works has examined abstract verbs in particular. For verb stimuli, the empirical focus has been on sensorimotor and embodied effects in action verbs (Aziz-Zadeh, Wilson, Rizzolatti, & Iacoboni, 2006; Desai, Binder, Conant, & Seidenberg, 2010; Hauk, Johnsrude, & Pulvermüller, 2004; Kemmerer, Castillo, Talavage, Patterson, & Wiley, 2008). It is not clear whether other types of verbs may also be grounded in multimodal representations. This lack of research on more abstract verbs may also reflect a historic bias to focus on concrete word meanings in lexical–semantic research (verbs tend to be rated as less concrete than nouns; Bird, Franklin, & Howard, 2001), or the reliance on measures such as concreteness ratings, which were not collected with a specific focus on verb meaning (Brysbaert, Warriner, & Kuperman, 2014). That is, for concreteness and many other dimensions, ratings were collected on individual word items and the verb sense was not specified. However, relative embodiment ratings provide an opportunity to overcome this limitation, as they were collected specifically for verb meanings (Sidhu, Kwan, Pexman & Siakaluk, 2014) and provide a measure by which to investigate grounding of abstract verbs.

The present study

To test predictions derived from theories of abstract word representation, we investigated differences in response time and accuracy during a syntactic classification task (SCT) and differences in accuracy rates in a recognition memory task for three types of abstract verbs: verbs that refer to mental states of being, verbs that refer to emotional states of being and verbs that have no apparent relationship to human bodily experience. These three abstract verb types reflect the various representational systems outlined by multiple representation theories and supported by the cluster analyses discussed above: introspective grounding (mental state verbs), emotional affective grounding (emotional state verbs) and linguistic grounding (nonembodied verbs). If, as multiple representation theories would propose, abstract language is grounded in a combination of multimodal and linguistic representations, we expected verbs that are related to states of being in the body (i.e. mental and emotional states) to demonstrate facilitatory effects similar to those in previous research for words higher in arousal, sensory richness and embodiment. Conversely, nonembodied verbs may be processed more slowly, as they have less semantically rich representations, relying more exclusively on linguistic grounding. If emotional grounding is crucially important for the meanings of abstract words, as the AEA would suggest, then we expected that processing benefits may only be observed for the emotional abstract verbs.

We used two different versions of the SCT: a go/no-go SCT (Experiments 1 and 2), in which a participant is asked to decide if a given word is a verb, and a forced choice SCT (Experiment 3), in which a participant is asked to decide if a given word is a verb or noun. Go/no-go tasks have the advantage of generating faster responses, greater response accuracy and typically have fewer processing demands (Perea, Rosa & Gómez, 2002). This method encouraged participants to recruit properties or dimensions related to verb meaning consistently across all the experimental items. We employed the forced-choice SCT, as well as a recognition memory task, to test whether any observed effects are task invariant or, alternatively, task dependent. Finally, we conducted a novel test of the proposal that there is a role for words' associates in abstract word processing. That is, we investigated semantic richness effects for the *associates* of the target words (Experiment 4). To do so, we used a new set of free association norms generated by De Deyne, Navarro, Perfors, Brysbaert and Storms (2019). This analysis of associate richness effects allowed us to test whether and how associated information may drive processing and representation for abstract verbs. In this analysis, the prediction we derived from multiple representation theories was that nonembodied verbs may exhibit more reliance on linguistic associations than would the verbs with introspective or emotional meanings.

Experiment 1

Method

Participants Sixty-one participants (52 female; mean age 21.70 years old; $SD = 5.68$) took part in Experiment 1. Participants were undergraduate students at the University of Calgary who participated in exchange for bonus credit in a psychology course. All participants were fluent in English and had normal or corrected-to-normal vision.

Stimuli The stimuli for Experiment 1 were 140 verbs (four lists of 35 words) and 120 nouns (two lists of 60 words). Characteristics for all word types are presented in Table 1. To select the verb stimuli for the present study, we began with the set of 687 verbs for which embodiment ratings are available (Sidhu et al., 2014). From this list, our goal was to distinguish four types of verbs: high-embodiment verbs (hereafter referred to as embodied verbs), mental state abstract verbs, emotional abstract verbs and nonembodied abstract verbs. Verb types were identified based on significant differences in three different semantic dimensions: cognitive ratings (collected for the purposes of the present study), valence ratings (Warriner et al., 2013), and embodiment ratings (Sidhu et al., 2014). Cognitive ratings were collected from a separate group of 25 participants on a subset of 241 low-embodiment, neutrally valenced verbs. Participants rated the degree to which each verb was cognitive in nature, using a scale of 1 (not cognitive) to 7 (fully cognitive), with cognitive defined as relating to mental actions or processes of acquiring knowledge and understanding through thought and experience. Embodied verbs had significantly higher embodiment ratings than the verbs in all other categories. Emotional abstract verbs had significantly lower valence ratings than the verbs in all other categories, indicating they were negatively valenced. Mental state and nonembodied abstract verbs had significantly different cognitive ratings from one another, with mental state abstract verbs having significantly higher cognitive ratings than nonembodied abstract verbs.

Table 1 Mean and standard deviations for experimental stimuli by word type

Word type ($n=35$ per verb type, 60 per noun type)	EMB Mean *SD*	VAL Mean *SD*	Freq Mean *SD*	AoA Mean *SD*	Length Mean *SD*	COG Mean *SD*	BOI Mean *SD*
Emotional abstract verbs	3.13 *0.32*	2.97[b] *0.43*	2.42 *0.69*	8.51 *1.93*	5.86 *1.67*	n/a	n/a
Mental abstract verbs	3.08 *0.38*	5.99 *0.34*	2.70 *1.00*	8.54 *2.41*	5.86 *1.44*	5.00[c] *0.57*	n/a
Nonembodied abstract verbs	3.21 *0.56*	5.98 *0.32*	2.58 *0.97*	8.27 *2.15*	5.57 *1.24*	3.33 *0.54*	n/a
Embodied verbs	5.01[a] *0.82*	6.08 *0.40*	2.48 *0.73*	7.82 *1.81*	5.74 *1.46*	n/a	n/a
High BOI nouns	n/a	5.18 *1.27*	2.51 *0.70*	8.17 *2.25*	5.67 *1.95*	n/a	3.43[d] *0.12*
Low BOI nouns	n/a	5.60 *1.02*	2.53 *0.84*	8.27 *2.76*	5.50 *1.49*	n/a	1.46 *0.22*

EMB embodiment, *VAL* valence, *Freq* frequency, *AoA* age of acquisition, *COG* cognitive, *BOI* body–object interaction

[a]Indicates that the embodiment ratings for the embodied verbs are significantly different than all other word types ($p<.05$)

[b]Indicates that the valence ratings for the emotional abstract verbs are significantly different than all other word types ($p<.05$)

[c]Indicates that the cognitive ratings for the mental state abstract verbs are significantly different from the non-bodily abstract verb types ($p<.05$)

[d]Indicates that the body–object interaction ratings for the high BOI noun type are significantly different from the low BOI noun type ($p<.05$)

Two different types of nouns were also identified: high body–object interaction (BOI) (Bennett, Burnett, Siakaluk, & Pexman, 2011; Tillotson, Siakaluk & Pexman, 2008) and low BOI nouns. BOI ratings were used to provide an approximate match to the relative embodiment of the different verb groups, as relative embodiment ratings only exist for verbs. All stimuli were matched on other dimensions that typically affect lexical processing (Brysbaert et al., 2011; Sidhu et al., 2016) including: word frequency (log subtitle frequency; Brysbaert & New, 2009), age of acquisition (Kuperman, Stadthagen-Gonzalez, & Brysbaert, 2012) and word length. The stimuli are listed in "Appendix A" (verbs) and "Appendix B" (nouns).

Procedure Participants completed a go/no-go SCT on a computer in our laboratory. They were instructed to look at each presented word and determine if it was a verb. If the word was a verb, they were asked to respond by pressing "k" on the keyboard and if the word was not a verb they were to make no response. Stimuli were presented in 24-point Times New Roman font in white letters on a black background using E-Prime 2.0 software (Psychology Software Tools, Pittsburgh, PA). Each trial began with a blank screen for 500 ms, followed by a fixation cross for 500 ms and then a word replaced the fixation cross, remaining on the screen for 3000 ms or until the participant made a response. Participants were asked to respond as quickly and accurately as possible. They received ten practice trials with feedback prior to beginning the experiment and received a break halfway through the experiment.

Results

All analyses were conducted using the statistical software R (R Core Team, 2013), the lme4 package (Bates, Maechler, Bolker, & Walker, 2015), the lmerTest package (Kuznetsova, Brockhoff, & Christensen, 2017) and the afex package (Singmann, Bolker, Westfall, Aust, & Ben-Shachar, 2019). We fit fixed effects corresponding to our experimental manipulation of word type (see Meteyard & Davies, 2020 and Winter, 2020). Trial-level data for all analyses reported here can be found at https://osf.io/9tcdv/. In the analysis of all verb response times, 327 incorrect trials (3.8%) were excluded as well as 264 trials (3.1%) on which response times were more than 3 *SD* away from a participant's mean. After removing these trials 7,949

Table 2 Experiment 1 mean response times, standard deviations, and accuracy in the SCT

Verb type	Mean response time (ms)	Response time SD (ms)	Mean accuracy (%)	Accuracy SD (%)
Abstract emotional state verbs	893.82	369.67	95.88	4.80
Abstract mental state verbs	861.23	358.85	97.85	3.60
Abstract nonembodied verbs	912.21	391.55	95.04	5.57
Embodied verbs	889.35	345.86	95.93	5.02

SCT syntactic classification task

Table 3 Experiment 1 linear mixed effects model estimates of verb type on SCT response time

Random effect			Variance			*SD*
Item intercept			7034			83.87
Subject intercept			30,431			174.44
Residual			98,636			314.06
Model	Reference group	Fixed effect	*b*	*SE*	*t* statistic	*p* value
1	Abstract mental	Emotional	36.68	22.38	1.64	.104
		Nonembodied	58.08	22.40	2.59	.011*
		Embodied	33.76	22.38	1.51	.134
2	Abstract emotional	Nonembodied	21.41	22.43	0.95	.342
		Embodied	− 2.92	22.41	− 0.13	.897
3	Abstract nonembodied	Embodied	− 24.32	22.43	− 1.09	.280

Redundant contrasts from the models have been omitted from this table. Random effects are consistent across all three models

SCT syntactic classification task, *SD* standard deviation, *SE* standard error

*$p < .05$

verb trials remained in the analysis. Noun trials were not analysed as no response time data were collected for these in the go/no-go task design. The mean SCT response time, accuracy and standard deviations by verb type are presented in Table 2.

We compared SCT response times[1] between the different types of verbs using three linear mixed effects models, with each model using one of the three abstract verb types as the reference group (dummy coded). Subject and item were entered as random intercept effects in each model and pairwise contrasts of verb type as fixed effects. Overall, abstract mental words had the fastest mean response time, however only one significant difference emerged between the abstract verb types; abstract nonembodied verbs were responded to significantly more slowly than abstract mental state verbs, $t(129.66) = 2.59$, $p = .011$. See Table 3.

Experiment 2

The purpose of Experiment 2 was twofold; first, we attempted to replicate the observed effects for mental state abstract verbs relative to nonembodied abstract verbs from Experiment 1. Second, we investigated whether the processing benefit for mental state abstract verbs would generalize to other cognitive tasks, in this case a memory task. If the observed processing benefit for mental state abstract verbs can be attributed to a distinct system of representation we would expect that memory performance for this verb type would differ from that of the other abstract verb types.

Method

Participants One-hundred and five participants (91 female; mean age 20.37 years old; $SD = 3.64$) took part in Experiment 2. Participants were undergraduate students at the University of Calgary who participated in exchange for bonus

[1] The response time data from Experiments 1–3 exhibited a positive skew. Supplementary analyses using a log-transformed response time for all mixed effect models reported here found that all significant fixed effects remained when using the log-transformed response time, with the exception of the significant difference between nonembodied abstract verbs and embodied verbs reported for Experiment 2. This effect was also not present in Experiment 1, which likely indicates this is not a strong or reliable effect as discussed in the discussion section.

Table 4 Experiment 2 mean response times, standard deviations and accuracy on the SCT

Verb type	Mean response time (ms)	Response time *SD* (ms)	Mean accuracy (%)	Accuracy *SD* (%)
Abstract emotional state verbs	1212.84	541.10	90.57	10.23
Abstract mental state verbs	1200.39	549.86	91.62	10.67
Abstract nonembodied verbs	1252.94	554.32	89.17	10.80
Embodied verbs	1203.89	523.40	91.73	9.64

SCT syntactic classification task

credit in a psychology course. All participants were fluent in English and had normal or corrected-to-normal vision.

Stimuli The stimuli for Experiment 2 included the same 140 verbs and 70 of the 120 nouns as Experiment 1. The verb stimuli were divided into two lists of 70 verbs with equal numbers of each abstract verb type in a way that maintained the verb type significant differences from Experiment 1. The same list of 70 nouns was added to each of the two verb lists and participants received one of the resulting two lists for an encoding phase. For the recognition memory portion of the study, participants saw both verb lists, one of which they had seen during the encoding task and the other which they had not seen (counterbalanced across participants). To ensure a similar number of previously seen recognition trials per item as Experiment 1, we increased the sample size here to 105.

Procedure The experiment was administered online (Qualtrics, Provo, UT). Participants were first presented with the encoding task, similar to the SCT used in Experiment 1, but with slight changes to accommodate administering the study online. Participants were instructed to look at each presented word and determine if it was a verb. If the word was a verb, they were asked to respond by pressing “k” on the keyboard and to make no response if the word was not a verb. Each trial began with a blank screen for 1000 ms and then a word appeared on the screen, remaining on the screen for 3000 ms or until the participant made a response. Each word was presented at the centre of the screen in the default text format for Qualtrics (Helvetica Neue, 24 point font). Participants were asked to respond as quickly and accurately as possible. They received 10 practice trials with feedback prior to beginning the experiment and completed a total of 140 trials (70 verb, 70 noun). The participants then completed a distractor task for 5 min, during which they answered a series of addition questions. After 5 min, they were automatically advanced to the recognition memory phase of the study. Participants were instructed to look at each word and determine if they had seen this word in the previous task (the encoding phase) or if it was a new word. If they had seen the word during the encoding phase, they were asked to respond by pressing "e" on the keyboard and if they had not seen the word earlier they were asked to respond by pressing the "i" key. Each word was presented in the centre of the screen until the participant made a response. Participants completed 140 recognition memory trials (70 previously seen verbs, 70 new verbs).

Results

Participants were excluded from the analysis if they did not complete 100% of the encoding task, as they needed prior exposure to the experimental stimuli to complete the recognition memory task. This resulted in the removal of 11 participants, leaving 94 participants (47 per each verb list at encoding) in the analysis.

We first conducted an analysis of the encoding task, to determine if the advantage for abstract mental state verbs relative to abstract nonembodied verbs, observed in Experiment 1, was replicated. In the analysis of all verb response times during the encoding task, 605 incorrect trials (9.19%) were excluded as well as 91 trials (1.36%) on which response times were more than 3 *SD* away from a participant’s mean. After removing these trials, 5894 verb trials remained in the analysis. Noun trials were not analysed as no response time data were collected for these in the go/no-go task. The mean SCT response times and standard deviations for each verb type are presented in Table 4. Response times were numerically slower than in Experiment 1 and accuracy rates were lower. In the case of the response times, this is likely due to slower response logging via Qualtrics, as the slower response times are consistent across all verb types. Lower accuracy rates likely reflect the difference between conducting the study in the laboratory setting versus online, with more potential distractions in the online version depending on where the participant chose to complete the study.

We used the same approach to the analyses as in Experiment 1. Two significant differences emerged: abstract nonembodied verbs were again responded to significantly more slowly than abstract mental state verbs, $t(132.77) = 2.21$, $p = .029$ and embodied verbs were responded to significantly faster than abstract nonembodied verbs, $t(132.8) = -2.07$, $p = .040$. See Table 5.

We next examined the differences in recognition memory performance amongst the three abstract verbs types and the

Table 5 Experiment 2 linear mixed effects model estimates of verb type on SCT response time

Random effect			Variance			*SD*
Item			5998			77.45
Subject			91,888			303.13
Residual			199,654			446.83
Model	Reference group	Fixed effect	*b*	*SE*	*t* statistic	*p* value
1	Abstract mental	Emotional	6.67	24.78	0.27	.788
		Nonembodied	54.92	24.86	2.21	.029*
		Embodied	3.47	24.75	0.14	.889
2	Abstract emotional	Nonembodied	48.25	24.91	1.94	.055
		Embodied	− 3.20	24.80	− 0.13	.897
3	Abstract nonembodied	Embodied	− 51.45	24.86	− 2.07	.040*

Redundant contrasts from the models have been omitted from this table. Random effects are consistent across all three models

SCT syntactic classification task, *SD* standard deviation, *SE* standard error

*Indicates $p < .05$

Table 6 Experiment 2 mean *d*-prime and standard deviations on the recognition memory task

Verb type	Mean *d*-prime	*d*-prime *SD*
Abstract emotional state verbs	1.47	1.22
Abstract mental state verbs	1.22	1.11
Abstract nonembodied verbs	1.33	0.82
Embodied verbs	1.57	1.16

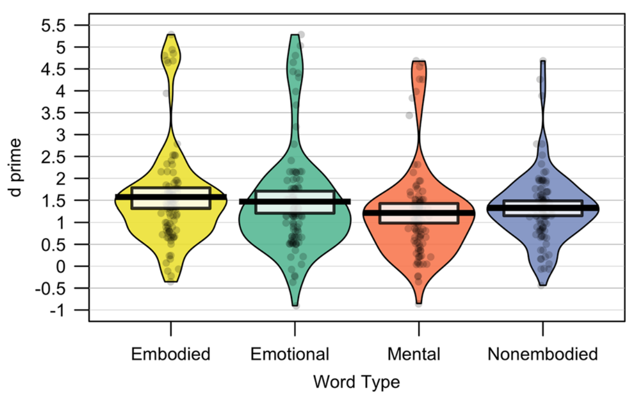

Fig. 1 Mean *d*-prime for each verb type. Boxes represents the 95% confidence interval. Individual dots represent participant means and violin shape represents density of participant means

embodied verb type. In keeping with the common practice in the memory literature, we calculated d-prime for each participant for each verb type, as a measure of memory accuracy. *D*-prime was calculated by taking the *z*-scored hit rate (percent of trials on which a previously seen word was correctly identified as an old word) minus the z-scored false alarm rate (percent of trials on which a new word was incorrectly identified as an old word). Lower *d*-prime values reflect less accurate memory performance. The mean *d*-primes and standard deviations for each verb type are presented in Table 6.

A repeated-measures ANOVA showed a significant main effect of verb type, $F(3, 279) = 3.97$, $p = .009$, partial $\eta^2 = 0.04$ (Fig. 1). Pairwise comparisons were conducted to compare all verb types to the abstract mental state verb type, using a Bonferroni corrected alpha of 0.017 to control for multiple comparisons. Recognition was significantly less accurate for abstract mental state verbs ($M = 1.22$, $SD = 1.11$) than for embodied verbs ($M = 1.57$, $SD = 1.16$), $F(1, 93) = 8.67$, $p = .004$, partial $\eta^2 = 0.09$.

Experiment 3

The purpose of Experiment 3 was to again examine the processing of different types of abstract verbs, but under different task demands. We used the same SCT task from Experiment 1 but adjusted the response to be forced choice rather than go/no-go. Thus, participants were asked to decide if a word was a verb or a noun.

Method

Participants Forty participants (39 female; mean age 21.60 years old; $SD = 6.05$) took part in Experiment 3. Participants were undergraduate students at the University of Calgary who participated in exchange for bonus credit in a psychology course. All participants were fluent in English and had normal or corrected-to-normal vision.

Stimuli The stimuli for Experiment 3 included the same 140 verbs and 120 nouns as Experiment 1.

Table 7 Experiment 3 mean response times, standard deviations, and accuracy on the SCT

Word type	Mean response time (ms)	Response time *SD* (ms)	Mean accuracy (%)	Accuracy *SD* (%)
Abstract emotional state verbs	916.13	375.49	88.29	9.98
Abstract mental state verbs	923.29	372.84	88.64	10.60
Abstract nonembodied verbs	940.64	383.21	82.14	12.31
Embodied verbs	933.98	374.43	83.64	11.81
High BOI nouns	924.49	350.14	92.29	8.01
Low BOI nouns	984.94	409.79	79.38	13.35

SCT syntactic classification task, *BOI* body–object interaction

Table 8 Experiment 3 linear mixed effects model estimates of verb type on SCT response time

Random effect	Variance	*SD*
Item	3533	59.44
Subject	27,074	164.54
Residual	112,833	335.91

Model	Reference group	Fixed effect	*b*	*SE*	*t* statistic	*p* value
1	Abstract mental	Emotional	− 5.52	19.68	− 0.28	.780
		Nonembodied	23.09	19.88	1.16	.248
		Embodied	10.29	19.85	0.52	.605
2	Abstract emotional	Nonembodied	28.61	19.90	1.44	.153
		Embodied	15.81	19.87	0.80	.428
3	Abstract nonembodied	Embodied	− 12.80	20.07	− 0.64	.525

Redundant contrasts from the models have been omitted from this table. Random effects are consistent across all three models

SCT syntactic classification task, *SD* standard deviation, *SE* standard error

Table 9 Experiment 3 linear mixed effects model estimates of word type on SCT response time

Random effect	Variance	*SD*
Item	8505	92.22
Subject	25,669	160.22
Residual	110,099	331.81

Reference group	Fixed effect	*b*	*SE*	*t* statistic	*p* value
Nouns	Verbs	− 31.65	13.56	− 2.33	.020*

SCT syntactic classification task, *SD* standard deviation, *SE* standard error

*Indicates $p < .05$

Procedure The procedure was the same as that described for Experiment 1 except that here if the word was a verb, participants were asked to respond by pressing “k” on the keyboard and, if the word was a noun, to respond by pressing the "d" key, with the response keys counterbalanced across participants.

Results

We first analysed the verb SCT responses in the same way as in Experiments 1 and 2. We then conducted a linear mixed effects analysis with both noun and verb trials. In the verb analysis 802 incorrect trials (14.32%) were excluded as well as 66 trials (1.38%) on which response times were more than 3 SD away from a participant’s mean. After removing these trials, 4,732 trials remained in the verb analysis. In the noun and verb analysis 1,482 incorrect trials (14.25%) were excluded as well as 115 trials (1.29%) on which response times were more than 3 SD away from a participant's mean. After removing these trials, 8,918 trials remained in the noun and verb analysis. The mean response times, accuracies and standard deviations for each word type are presented in Table 7.

The model results for verbs are presented in Table 8. Under these task demands, there were no significant differences amongst the verb types.

We next compared SCT response times between nouns and verbs using a linear mixed effects model with nouns as the reference group. Subject and item were entered as random intercept effects and a contrast of word type (noun or verb) as a fixed effect. Verbs were responded to significantly faster than nouns, $t(248.51) = -2.33$, $p = .020$. See Table 9.

The results of three experiments show evidence that, at most, modest differences in processing can be observed amongst the three different types of abstract verbs and that these differences are modulated by task demands. The representational underpinnings of mental state abstract verbs appear to afford an advantage in the SCT and a disadvantage in a memory task. The results from Experiment 3 further qualify these differences, demonstrating that verbs as an entire syntactic group are afforded an advantage relative to nouns in the SCT, suggesting that processing differences between abstract verb types may only emerge when participants are focused on processing verb-only meaning, as in the go/no-go task design.

To further examine processing and representation of abstract verbs, in the final experiment we adopted a semantic richness approach with a novel twist, focusing on semantic richness effects of a verb's associates. This shifts the traditional focus on a target word's characteristics to consider whether the target word's associates' semantic characteristics affect processing. It has been proposed that when processing abstract words (particularly abstract words in isolation), highly associated words may come to mind, though the degree to which the semantic information of associated words is activated is the subject of some debate (Barsalou & Wiemer-Hastings, 2005). In Experiment 4, we tested this proposal by investigating whether the semantic characteristics of associates matter for target word processing in an SCT.

Experiment 4

Method

We investigated semantic richness effects for linguistic associates of abstract verbs. To do so we used associates derived from a large-scale free association norms dataset (Deyne et al., 2019), in which participants were asked to list up to three words that come to mind when reading a target word. As described below, some of our verb stimuli were not in the De Deyne dataset and so we first collected association data for those items. After collecting those additional associations, we ran a linear mixed effects model on the SCT data collected in Experiment 1.[2] For each abstract verb in the original stimuli list we extracted the top three associates listed in the first position and calculated the average across those associates for the following lexical and semantic dimensions: frequency (Brysbaert & New, 2009), prevalence (Brysbaert, Mandera, McCormick, & Keuleers, 2019), age of acquisition (Kuperman et al., 2012), semantic diversity (SemD; a measure of the extent that a word appears in diverse contexts; Hoffman, Lambon Ralph, & Rogers, 2013), average neighbourhood similarity (ANS; the mean distance between a word and all words within its semantic neighbourhood; Shaol & Westbury, 2010), concreteness (Brysbaert et al., 2014) and valence (Warriner et al., 2013). We did not include variables related to our target stimuli themselves, as the stimuli do not vary freely on the semantic dimensions used to classify them into subsets of abstract verbs. We did, however, include abstract verb type in our model, to test whether the dimensions of the associates matter differentially depending on the type of abstract verb. Of our target stimuli, 13 verbs and 15 nouns were not included in the De Deyne et al. dataset. For these words we collected associates using the same instructions as De Deyne et al.

Participants One hundred and fifty-eight participants (142 female; mean age 20.48 years old; SD = 3.42) took part in Experiment 4. Participants were undergraduate students at the University of Calgary who participated in exchange for bonus credit in a psychology course. All participants were fluent in English and had normal or corrected-to-normal vision.

Stimuli The stimuli for Experiment 4 were 28 verbs from the original Experiment 1 stimuli list that were not part of the De Deyne et al. (2019) dataset and 18 verbs (three per verb type) from Experiment 1 that were in the De Deyne et al. dataset, included for validation purposes.

Procedure Participants completed the free association task via an online study (Qualtrics, Provo, UT). They were presented with a cue word at the top of the screen and instructed to enter the first word that came to mind when reading the cue word. They were then instructed to enter the next word that came to mind, and one more, for a maximum of three words. They would choose "I have entered all my

[2] Mixed effect models were also conducted using the response data for the Experiment 2 encoding task and the SCT from Experiment 3. Those results are consistent with the AoA and concreteness effects reported here. The frequency of associates effect from Experiment 1 was not replicated in the data from Experiment 2 or 3.

Table 10 Linear mixed effects model estimates of verb type and associate features on SCT response time from Experiment 1

Random effect		Variance			*SD*
Item intercept		3694			60.78
Subject intercept		33,231			182.29
Residual		101,108			317.97
Fixed effect	***b***	***SE***	***t* statistic**	***p* value**	**VIF**
Nonembodied vs mental state	24.31	19.04	1.28	.205	3.52
Emotional vs mental state	67.17	27.82	2.42	.018*	
Associates frequency	−45.81	10.06	−4.56	<.001***	1.93
Associates AOA	−16.80	12.73	−1.32	.190	3.12
Associates concreteness	32.29	7.95	4.06	<.001***	1.23
Associates valence	25.88	12.86	2.01	.047*	3.17
Nonembodied vs mental state × associates AOA	−54.64	19.29	−2.83	.006**	2.61
Emotional vs mental state × associates AOA	10.05	17.35	0.58	.564	

SCT syntactic classification task, *SD* standard deviation, *SE* standard error, *VIF* variance inflation factor, *AoA* age of acquisition

*$p<.05$, **$p<.01$, ***$p<.001$

responses" once they had entered three words or could not think of any more words in order to proceed to the next page. If participants did not know a cue word they were instructed to select "Unknown word" as their response to continue to the next page. Each cue word was presented on the centre of the screen in the default font for Qualtrics (Helvetica Neue) in 36 point font size.

Results

We excluded one participant who did not provide consent in the online study and four participants who elected to do a study alternative (an article review and discussion). Based on the exclusion criteria applied by De Deyne et al. (2019), we then excluded the data for participants who provided no associates or had indicated "Unknown word" for more than 60% of the cue words (eight participants), and for participants who gave more than 30% of their responses as multi-word expressions (four participants). We also excluded one cue word (berth) that had less than 60 first associates (i.e. associates provided as the first word that came to mind). For each cue word, the frequency of each unique first associate was calculated. The top first associates for each of the 16 validation cue words were compared to the top first associates for the same cue words from the De Deyne et al. (2019) dataset. Of the 16 validation words, 7 shared the exact same top three first associates as De Deyne et al. For the remaining nine words, we examined the range in our associates' data required to capture the top three first associates from the De Deyne et al. dataset. This ranged from a minimum of the top four most frequent associates in our list (two items; cub and noon) to a maximum of the top ten most frequent associates in our list (two items; aid and exist).

We calculated an associate's value for each lexical and semantic dimension of interest by taking an average of the dimension value for the top three associates of each abstract verb in our stimuli set. All dimensions were *z*-scored and entered as predictors into a linear mixed effects model, along with target verb type, using mental state verbs as the reference group as they were the only group to show significant differences compared to other verb groups in Experiments 1 and 2. Likelihood ratio tests were conducted to determine whether a given predictor and the associated interactions should be included in the final model. These tests resulted in a final model that included fixed effects of verb type, frequency of associates, age of acquisition of associates, concreteness of associates, valence of associates and an interaction between verb type and age of acquisition of associates.

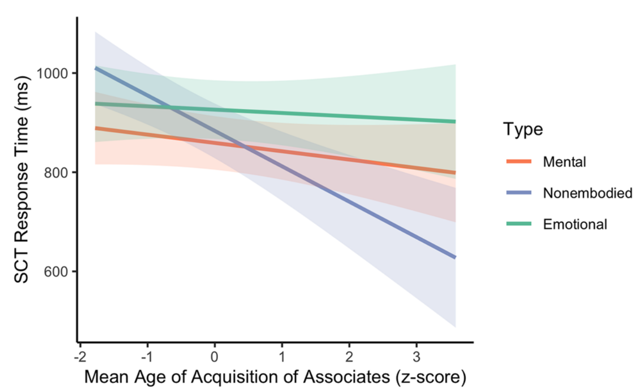

Fig. 2 Effect of verb type by item associates' mean age of acquisition on SCT response time. Bands represent 95% confidence intervals

The results of the final model are presented in Table 10. One significant difference emerged for verb type contrasts: emotional state verbs were responded to more slowly than mental state verbs, $t(91.62) = 2.42$, $p = .018$. Two significant main effects and one significant interaction emerged that demonstrated semantic richness effects of the target verbs' associates. First, abstract verbs whose associates had higher mean frequency were responded to more quickly, $t(92.58) = -4.56$, $p < .001$. Second, abstract verbs whose associates had higher mean concreteness were responded to more slowly, $t(93.03) = 4.06$, $p < .001$. Finally, nonembodied verbs whose associates tended to be acquired later (had an older mean AoA) were processed more quickly than those with earlier acquired associates, $t(92.08)$, -2.83, $p = .006$, see Fig. 2.

Discussion

The purpose of the present study was to examine processing of three abstract verb types to better understand how they may draw upon multiple modal and linguistic representations. We tested for potential processing differences between mental, emotional and nonembodied abstract verbs using syntactic classification tasks and a memory task. The results of Experiments 1 and 2 suggested that there are indeed processing differences amongst types of abstract verbs, with nonembodied abstract verbs showing significantly slower response times than mental state abstract verbs in Experiment 1 and slower response times than both mental state abstract verbs and embodied verbs in Experiment 2. There were no significant differences between the other types of abstract verbs. However, the results of Experiment 3 suggested that faster processing for mental state abstract verbs is task dependent. A shift to a forced choice response in the SCT, rather than a go/no-go response, eliminated the processing benefit for mental state abstract verbs. This suggests that these differences are modest at best and that the "is it a verb?" decision encourages a participant to focus on verb-relevant information, which may contribute to processing differences for nonembodied abstract verbs.

The observed effect of verb type provides partial support for multimodal theories of semantic representation. First, the verb type likely to reflect introspective grounding (mental state abstract verbs) showed a predicted processing benefit relative to nonembodied abstract verbs. Second, faster processing of embodied verbs in Experiment 2 relative to nonembodied verbs further supported multimodal theories of semantic representation, as verbs with more information associated with the human body were processed more quickly than verbs lacking information associated with the human body. That said, this effect was not observed in all experiments, so this evidence should be interpreted with caution.

There were also no significant differences between responses to emotional abstract verbs and any other verb type. This is inconsistent with other research where processing advantages have been reported for emotion concepts. Kousta et al. (2011) found that after controlling for imageability and context availability, abstract words were processed more quickly than concrete words. They attributed this faster processing to the greater affective associations that abstract words have and thus proposed that emotional experience played a role in grounding abstract words. In the current study, we found no processing benefit for emotional abstract verbs; furthermore, emotional experience could not have been a factor in the observed mental state versus nonembodied verb differences, as valence was matched for these two verb types. This finding thus does not support predictions derived from the AEA; we found no evidence that abstract verb meaning is grounded via emotion systems.

The results of the memory task in Experiment 2 shed more light on the nature of the processing effects observed for mental state verbs. Recognition memory was significantly less accurate for mental state abstract verbs, relative to embodied verbs. Better memory performance for more embodied verbs has been demonstrated in previous research (Sidhu & Pexman, 2016), but the finding here is more specific. Coupled with the observed processing benefit for mental state abstract verbs in the SCT, it seems possible that there is some relative similarity or consistency in the meanings of mental state abstract verbs that produces a benefit in syntactic classification, but also makes these verbs more difficult to remember and differentiate from one another in recognition memory.

This similarity may be related to the fact that the meanings of the mental state verbs are all based in introspective experience. Perhaps, introspective experiences are less variable than emotional or sensorimotor experiences. The precise nature of the relative similarity within the category of mental state abstract verbs is difficult to pinpoint. We did consider the possibility that higher similarity within the mental state verb type might be evident in terms of shared associates. We conducted a pos hoc analysis of the frequency of shared associates by verb type, with frequency indexed by the number of times each associate appears within the top three associates of all items for the same verb type. Four extreme outliers that had associates occurring more than 12 times within their own verb type were removed from the embodied verbs. An ANOVA on the remaining values for each verb type showed a significant main effect for within-type associate frequency, $F(3,132) = 3.47$, $p = .018$; however, the only significant difference that emerged in follow-ups was between nonembodied and emotional state verbs, $t(132) = -2.95$, with a Tukey-adjusted p value of $p = .019$.

We also examined the number of times a target item itself appeared as an associate for other items within each verb type. This ANOVA revealed no significant differences between verb types, $F(3,132) = 1.43$, $p = .237$. These post hoc findings would suggest that shared associative structures do not drive the fluency we observed in semantic processing for mental state verbs.

It also seemed possible that within-category similarity for mental state abstract verbs might be related to the fact that with internal, introspective state meanings, any change of state generally occurs to or within the agent itself. Processing differences between internal and external change of state verbs have been demonstrated in lexical decision times, with longer response times for external change of state verbs (McKoon & Macfarland, 2002). These LDT results would be consistent with our findings if mental state verbs predominantly represent internal changes of state. This distinction of internal vs external relation to an individual has also been recently identified as an important dimension to abstract concept representation generally (Vargas & Just, 2019). The mental state abstract verbs also lack any kind of valence or other episodic memory that can distinguish their representations, which could hinder the ability to remember them. While promising, these explanations for the seemingly homogeneous subset of mental state verbs within the larger heterogenous array of abstract verbs are admittedly speculative and need to be investigated more systematically before drawing strong conclusions about the cause of the observed effects.

In Experiment 4, we investigated the semantic richness effects of verbs' associates themselves on SCT response times, to determine whether these linguistic relationships are an important factor in abstract verb representation. Previous research indicates that abstract concepts rely more on associations in their representations than do concrete concepts, but it has been assumed that only surface-level, phonological elements of associates are engaged when processing abstract concepts, with minimal access to the semantic content of the associates (Barsalou & Wiemer-Hastings, 2005). To test this, we analysed semantic richness effects of verbs' associates on a target verbs' response times. Contrary to the findings of Experiment 1 and Experiment 2, this analysis showed a processing advantage for mental state verbs in comparison to emotional state verbs, rather than nonembodied verbs. The addition of other predictors into the mixed effects model and the elimination of contrasts to embodied verbs may have changed the relationship between verb type and response time, revealing a previously undetected significant difference between these abstract verb types. We also found that semantic dimensions of associates are related to target verb response times: items whose associates were more frequent were responded to more quickly (though this effect only emerged in the Experiment 1 data), and items whose associates had higher concreteness were responded to more slowly in the SCT. We further observed an interaction between the nonembodied abstract verbs and associates' age of acquisition, with faster responses to nonembodied abstract verbs whose associates had an older age of acquisition.

These findings are striking, as they are the first indication that the semantic dimensions of an item's associates may influence processing of the target item itself. Furthermore, the pattern of relationships provides an interesting view of the nature of the representational structure of these abstract verbs and of the most nonembodied verbs in particular. That is, the results suggest that dimensions reflecting more linguistic experience (for instance, older age of acquisition and less concrete associates) contribute to faster response times. This finding could be accommodated by multiple representation theories of semantic representation, which emphasize that linguistic experience remains an important aspect of abstract concept representation, alongside other modalities such as emotional and sensorimotor. In such a case, it would make sense that the nonembodied abstract verbs would benefit the most from this increased linguistic experience reflected by their associates, as they have less emotional or sensorimotor experiences to ground their meanings.

Certainly, there are some limitations in the extent to which the results of the present study can be generalized. Verbs possess a number of unique dimensions such as lexical aspect, tense, regularity, etc. There is evidence that these unique distinctions contribute to semantic processing, particularly for verbs processed in isolation (Gennari & Poeppel, 2003; Sidhu et al., 2016) and our findings from Experiment 3 suggest that there is something unique to processing verb meaning that highlights this difference in abstract verb representations. In the present study, while all verbs were presented in present tense, there were no controls for aspect or regularity in the stimuli selection process. In future work, controlling for stative vs dynamic verbs or internal vs external change of states across verb types may aid in determining the cause of the syntactic categorization advantage observed for mental state verbs.

Furthermore, the findings are limited to a relatively small subset of abstract verbs. The major limit on the stimulus selection process was the size of norms available for verb stimuli specifically. Indeed, some of the items we selected are not solely classified as verbs or classified as verb-dominant in all part-of-speech databases (e.g. Brysbaert, New, & Keuleers, 2012). The fact that some of our items did not have verb-exclusive meanings was probably less of an issue in Experiments 1 and 2, where participants were directed to focus on verb meaning in the task. In Experiment 3, however, the forced choice task format asked participants to distinguish nouns and verbs and the inclusion of some items that had both noun and verb meanings might have made the task more difficult. This may explain why the differences in response time between mental state and nonembodied abstract verbs observed in Experiments 1 and 2 were not present in the forced choice task. To enable future research on the heterogenous space of abstract verb representation, it will be important to develop more verb stimuli so that processing for verb-dominant and verb-only items can be examined and compared systematically.

The results of the present study provide evidence that modest, task-dependent differences in processing can be detected for a subset of abstract verbs; in particular, those relating to mental states of being. We take this as weak evidence in support of multiple representation theories. In addition, we note that important dimensions that influence verb representation, such as aspect and internal/external change of state, have not yet been examined and should be taken into account in future research to further understand the underlying representational systems for this syntactic class.

Contrary to previous assumptions about the contribution of associates when processing abstract words (e.g. Barsalou & Weimer-Hastings, 2005), our findings also suggest that linguistic associations play an important role in abstract verb representation and that the semantic meaning of those associates matters, particularly for those concepts that are most disembodied. This novel finding provides a promising avenue to further investigate linguistic associations across other syntactic categories of abstract and concrete words. Finally, our findings underscore the importance of earlier calls for greater precision in how we consider abstract words (Borghi et al., 2017), as there remains much to be learned about semantic representation and processing by teasing apart different types of abstract words.

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Compliance with ethical standards

Conflict of interest Emiko J. Muraki declares that she has no conflict of interest. David M. Sidhu declares that he has no conflict of interest. Penny M. Pexman declares that she has no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee (Conjoint Faculties Research Ethics Board, REB14-1662) and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Informed consent Informed consent was obtained from all individual participants included in the study.

Appendix A

See Table 11.

Table 11 Verb stimuli

Mental state abstract	Emotional state abstract	Nonembodied abstract	Embodied
accept	accuse	aid	adapt
add	annoy	align	announce
amend	betray	allow	awaken
aspire	beware	arrive	build
assert	cheat	ascend	chatter
assess	complain	assist	clothe
assure	condemn	attain	communicate
attempt	criticize	attend	crave
be	deceive	begin	defend
become	delay	broaden	devour
choose	demolish	cater	dine
coax	deprive	dissolve	discuss
compose	detain	ease	dive
decide	detest	embark	doze
devote	disappoint	enroll	evolve
excel	disobey	evaporate	exercise
find	envy	extend	exhale
foresee	evict	fasten	exist
improve	fail	keep	feel
invest	forbid	make	float
locate	hate	occur	focus
memorize	ignore	pause	glide
motivate	lose	pave	greet
obey	mislead	regain	ingest
ponder	mourn	renew	meditate
predict	offend	restore	munch
prove	owe	retire	pray
publish	pester	return	recover
realize	pry	send	seek
reflect	quit	share	sketch
reveal	reject	show	snooze
solve	reprimand	simmer	sprint
transform	resent	spend	taste
unite	shun	sweeten	visit
want	spoil	toughen	wander

Appendix B

See Table 12.

Table 12 Noun stimuli

High BOI		Low BOI	
ale	medal	beaver	knack
ambulance	missile	beige	length
banner	moisture	berth	lightning
bay	mosquito	bliss	luck
birch	newt	breach	mauve
blob	pendulum	breadth	mode
brain	pint	brink	month
bureau	podium	brunt	night
cathedral	prison	chance	noon
certificate	projectile	creed	ode
chapel	rudder	dawn	peace
court	self	depth	plea
cub	shrine	deuce	prose
dame	silver	dinosaur	pun
den	skyscraper	dragon	rainbow
doctor	spa	drake	rhinoceros
dung	sport	dupe	scorpion
furnace	spud	elephant	south
gang	square	faith	speech
garage	stag	farce	squirrel
globe	temple	feat	stealth
grenade	thicket	fine	submarine
heart	thief	first	teal
highway	tomahawk	fond	theme
kelp	tomb	genie	third
king	tower	glad	trance
kit	trophy	gorilla	twelve
lobe	turpentine	guise	twinge
mantle	tweed	hertz	unicorn
mare	window	keen	volcano

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