OPEN ACCESS

Australian Journal of Applied Linguistics
ISSN 2209-0959
https://www.castledown.com/journals/ajal/

Australian Journal of Applied Linguistics, 6(3), 176–187 (2024)
https://doi.org/10.29140/ajal.v6n3.1003

Predicting English Word Concreteness Through Its Multidimensional Perceptual and Action Strength Norms

MOHSEN DOLATABADI

Tabita Modarres University, Department of Linguistics, Tehran, Iran
domohsen@yahoo.com

Abstract

Many datasets resulting from participant ratings for word norms and also concreteness ratios are available. However, the concreteness information of infrequent words and non-words is rare. This work aims to propose a model for estimating the concreteness of infrequent and new lexicons. Here, we used Lancaster sensory-motor word norms to predict the word concreteness ratios of an English word dataset. After removing the missing values, we employed a stepwise multiple linear regression (SW-MLR) procedure for choosing an optimum number of norms to develop a predictive multiple regression model. Finally, we validate our model using 10-fold cross-validation. The final model could predict concreteness by Residual Mean Standard Error equal to 0.723 and R-Square of 0.515. Also, our results showed that all 11 variables of this dataset except the Head-mouth parameter are useful predictors. In conclusion, as a growing demand to know the concreteness values of non-words and also infrequent words is evident, our statistical method can pave the way for controlled experiments when choosing non-words as a stimulus is critical.

Keywords: concreteness, prediction, perception, multiple linear regression.

Introduction

Why do people categorize some words as concrete and others as abstract? How can we predict the concept of concreteness value based on their embodied properties? The way we think about the world is intimately connected to our sensory-motor and action-effector perceptions, as suggested by Barsalou

(1999) and many other studies. These findings emphasize that when we conceptualize the world, we rely on the mechanisms that allow us to experience it firsthand. This process involves functional dependence on action, emotion, and perception systems (Barsalou, 2008). Our brains use representations rooted in experiential methods, employing neural simulations or reenactments to deploy these representations (Barsalou et al., 2003).

Embodied cognition is a well-supported concept (Barsalou, 1999; Connell, 2019; Connell & Lynott, 2014b; Smith & Gasser, 2005; Vigliocco, Meteyard, Andrews & Kousta, 2009; Wilson, 2002). It highlights that people perceive and understand the world through a combination of sensory-motor and action-effector perceptions. This perspective extends to mental representations of lexicons, as demonstrated by studies like Yao et al. (2020). Research has consistently shown that we comprehend language by relating it to our interaction with the world, exemplified by idiomatic metaphors that activate both sensory-motor and abstract concept networks in the brain (Hellmann et al., 2013). The conceptual metaphors offer valuable insights into individual differences, cognitive processes, and social interactions (Fetterman, French, and Meier, 2022; Gibbs, 2017).

One practical application of embodied cognition is seen in video instruction, which combines visual and auditory information to enhance learning (Lange & Costly, 2020). This approach embeds instructors' movements, gestures, and classroom space (Lim, 2021) to provide students with social and attentional cues, fostering a social partnership with the instructor and aiding comprehension of visual content (Stull et al., 2021). It emphasises the importance of concrete representations in contrast to abstract ones in lexicon representations.

The debate over why people from different cultures rank some words as more concrete than others persists (Hill et al., 2014; Vigliocco et al., 2014). However, it's generally agreed that concepts experienced by sensory-motor brain networks in the dorsal stream are considered more concrete. In linguistics studies, word concreteness is often determined by factors like imageability and contextual availability, where higher values indicate greater concreteness (Montefinese, 2019). Recent studies also indicate that the differentiation between concrete and abstract word representations in our brain involves the inferior frontal gyros, with abstract concepts showing more engagement in verbal regions (Wang et al., 2010).

Despite the availability of various datasets for common word concreteness evaluations (such as the Brysbaert dataset), predicting the concreteness of infrequent words and non-words is becoming increasingly essential to meet growing demands (Chuang et al., 2020). Even pseudo-words composed of sound strings have gained significance in psycholinguistic research, with recent computational models emphasizing their semantic relevance, thus necessitating a deeper understanding of their properties (Yu-Ying Chuang et al., 2020). Furthermore, many studies highlight the implications of specific language processing styles in various mental disorders, including Schizophrenia, Alzheimer's disease (AD), Parkinson's disease (PD), and Aphasia.

Among them, signs and symptoms of Schizophrenia can vary but usually involve delusions, hallucinations, or disorganised speech (McCutcheon et al., 2023). People with schizophrenia experience hallucinations, which can involve seeing or hearing things that do not exist. Hearing these voices might be the most common hallucination (Faden, 2023). Effective communication can be impaired when thoughts are disorganised, and answers to questions may be incomplete or unrelated in speech. It is possible to put meaningless words together in a speech that cannot be understood, sometimes called a word salad (Andreasen, 1979). In addition, the motor behaviour may be highly disorganised or abnormal, manifesting as childlike silliness or unpredictable agitation. Behaviour is not focused on a goal, so it is hard to accomplish tasks. An individual may resist instructions, have an inappropriate posture, have a complete lack of response, or have excessive and useless movement (Modesti et al., 2023). Also, schizophrenic people may have negative symptoms, such as neglect of personal hygiene or the appearance of lack of emotion (not making eye contact, not changing facial expressions, or speaking monotonously). Additionally, the individual may lose interest in everyday activities and withdraw socially. These symptoms are directly and indirectly effective in embodied representation of words.

Dyslexia and Schizophrenia affect the Magnocellular pathway that processes more global attentional scope (Grinter et al., 2010) also abstract and daily words (Peng et al., 2020; Krahmer, 2009) So that the correlation between representing abstract and concrete words and mental disorders (Binney et al., 2016) is obvious. An explanatory article (Ponari et al., 2018) shows that children with Developmental language disorders (DLD) only learn abstract concepts as much as ordinary children. Developmental language disorders (DLD) affect how children learn, understand, and use language. These language difficulties are not attributed to other conditions, such as hearing loss or autism, or extenuating circumstances, such as a lack of exposure to language (Zapparrata, 2023). Thus, having deep insight into pseudoword properties would help to better disease differential diagnosis (Hoffmann, 2011).

The other application of concrete and abstract recognition is in marketing, especially Neuromarketing (Bhardwaj, 2023). As a marketing discipline, neuromarketing applies neuroscience and cognitive science. Market research can provide insight into customers' needs, motivations, and preferences that conventional methods such as surveys and focus groups. To better understand how customers react at a non-conscious level, neuromarketing can be used to evaluate specific advertisements, marketing, packaging, content, etc. In this vein, concrete and abstract processings are vital. To be more precise, the lexical decision task provides researchers with pieces of evidence about the faster reaction time to the concrete lexicons in comparison with the abstract ones (Barber et al., 2013).

Furthermore, researchers demonstrate a link between labelling and consumer choices regarding concreteness (Hodel, Olszewska, & Falkowski, 2022; Jiang, & Punj, 2010). Combining these findings from Linguistics and Branding Sciences, including nonwords, pseudoword, and sound-symbolised word properties, we can efficiently label products to stand out from the others. An example of sound symbolism is the non-arbitrary mappings between speech sounds' phonetic properties and their meanings. Although the topic has received extensive literature, the acoustic and psychological mechanisms contributing to sound symbolism remain unclear (Suárez, 2022).

The new usages of this distinction between concrete and abstract words are for determining the perception of a text in terms of complexity levels (Solovyev et al., 2018) in the Educational Sciences. Text complexity is determined as the level of difficulty of reading and understanding of text regarding components like the readability of the text, the levels of meaning or purpose in the text, the structure of the text, the conventionality and clarity of the language, and the knowledge demands of the text (Benedetto, 2023).

In the study, a set of step-by-step linear regression models was created to determine the most reliable predictors of concreteness. A 10-fold cross-validation statistical analysis was then used to evaluate the performance of the best model in terms of prediction accuracy.

Method

The open access data used for this study included 40000 English words and their mean values of concreteness, as reported by Brysbaert et al. (2013), besides their perceptual strength and their action strength according to the Lancaster multimodal norms (Lynott, 2019). Essentially Brysbaert et al. conducted a new concreteness rating study in order to

1. obtain concreteness ratings for a much larger sample of English words,
2. obtain ratings from all kinds of experiences, and to
3. define a reference list of English lemmas for future research

We matched two datasets by removing uncommon words between two datasets in R statistical software using the tidyverse package in this software. Data science packages are part of the tidyverse, an opinionated collection of R packages. Then we replicated a well-known procedure used in Computational Chemistry (e.g., Dolatabadi et al., 2010; Nekoei et al., 2011). Since co-linearity is a deteriorating factor for the predictive models, we followed statistical criteria (e.g., Dohoo et al., 1997) to detect correlated independent variables, namely, variance inflation factor (VIF) near ten and a correlation coefficient above or equal to 0.9.

After removing the missing values, our data dimensions were 39702 * 12, tested for the co-linearity (coefficient ≥ 0.9) among variables, including the dependent concreteness variable and 11-word norms.

Multiple Linear Regression (MLR) Analysis

MLR is one of the most frequently used methods for determining competent variables for predicting the outcomes (Eberly, 2007).

It is a linear model extension that uses only one predictor:

$$\textbf{Concreteness} = \textbf{a0} + \textbf{a1} \cdot \textbf{d1} + \ldots + \textbf{an} \cdot \textbf{dn}$$

where a0 as the intercept and also the regression coefficients are assigned through the least-square methods. We used R software to develop MLR models.

Stepwise Multiple Regression

The forward and backward or generally stepwise multiple regressions are used for the inclusion of the best predictors. This technique begins from a null model and a full model to add or remove variables step-wisely, which results in the discovery of the best-fitted model by the AIC values (Heinze et al., 2018).

Cross-Validation Technique

To assess the consistency and reliability of a predictive method, researchers often employ cross-validation techniques. These techniques can be broadly categorized into two types: exhaustive and non-exhaustive cross-validation. Exhaustive cross-validation includes methods like Leave Percent Out (LPO) and its specific case, Leave One Out (LOO). On the other hand, non-exhaustive cross-validation methods encompass k-folds cross-validation and repeated random sub-sampling validation (Baumann, 2003). In our current study, we adopted a non-exhaustive cross-validation approach. Initially, we partitioned our dataset into two distinct subsets: a 20% test set and an 80% training set. The training set was the foundation for building our predictive model, allowing it to learn from the data. Subsequently, we employed the test data to evaluate the model's predictive performance (Baumann, 2003).

Results

Since collinearity among variables impairs model performance, we first computed correlation coefficients for all of the variables that resulted in no correlated variables. The conclusion is based upon the idea that if one variable increases as the other increases, the correlation between the two is positive; if one decreases as the other increases, the correlation is negative. An absence of correlation is an expression of 0 (Dormann et al., 2013).

The residual standard error, determining how well a regression model fit the dataset, of the calculated stepwise model was 0.7235 on 39691 degrees of freedom (maximum number of logically independent values) for the equation (1). For the model, the multiple R-squared was 0.5153, and the adjusted R-squared was equal to 0.5152, revealing that our calculated model was moderately good.

Eq (1):

Concreteness = 1.890 – 0.025 Auditory. mean + 0.025 Gustatory. mean + 0.294 Haptic. mean + 0.214 Olfactory. mean – 0.359 Interoceptive. mean + 0.337 Visual. mean – 0.053 Foot-leg. mean + 0.074 Hand-arm. mean – 0.028 Head. mean + 0.210 Torso. Mean

After calculating VIF(a measure of multicollinearity amount in the regression variables**)** for our model (Fig. 2), none of the variables had near ten quantities (Alin, 2010), a fact that made us approve all independent variables in the step-wise model.

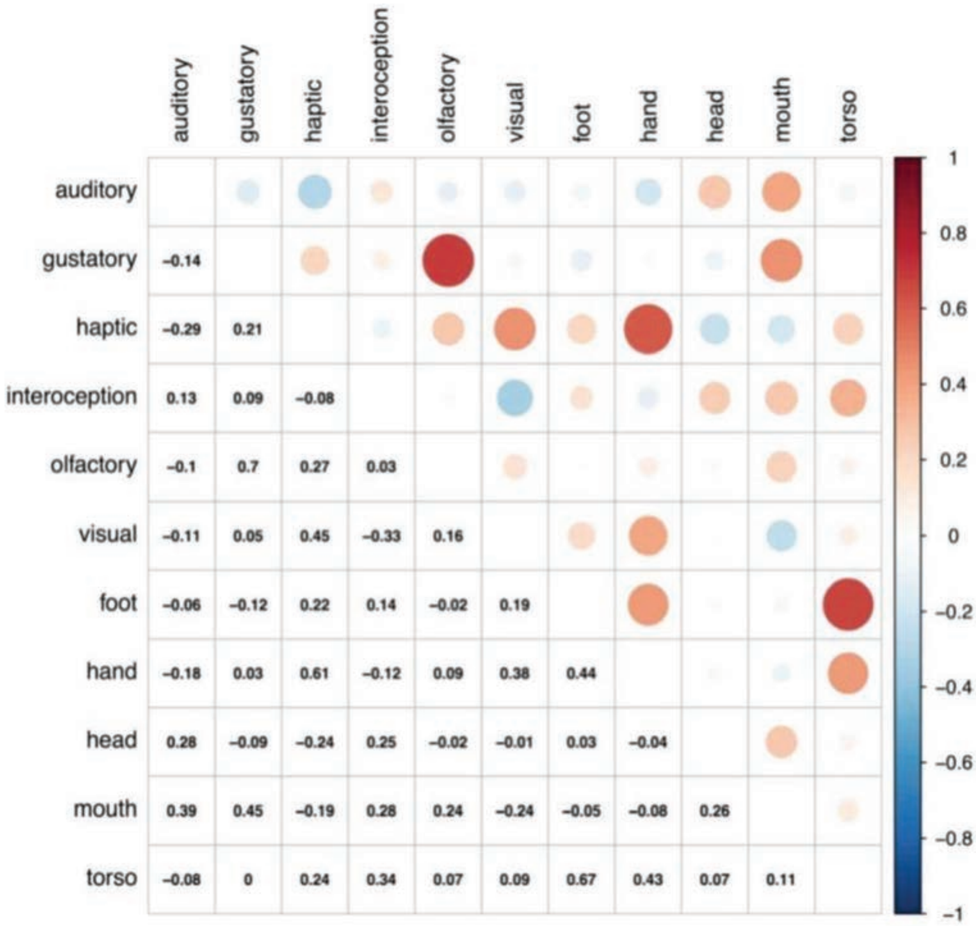

Figure 1 Correlation matrix for all variables.

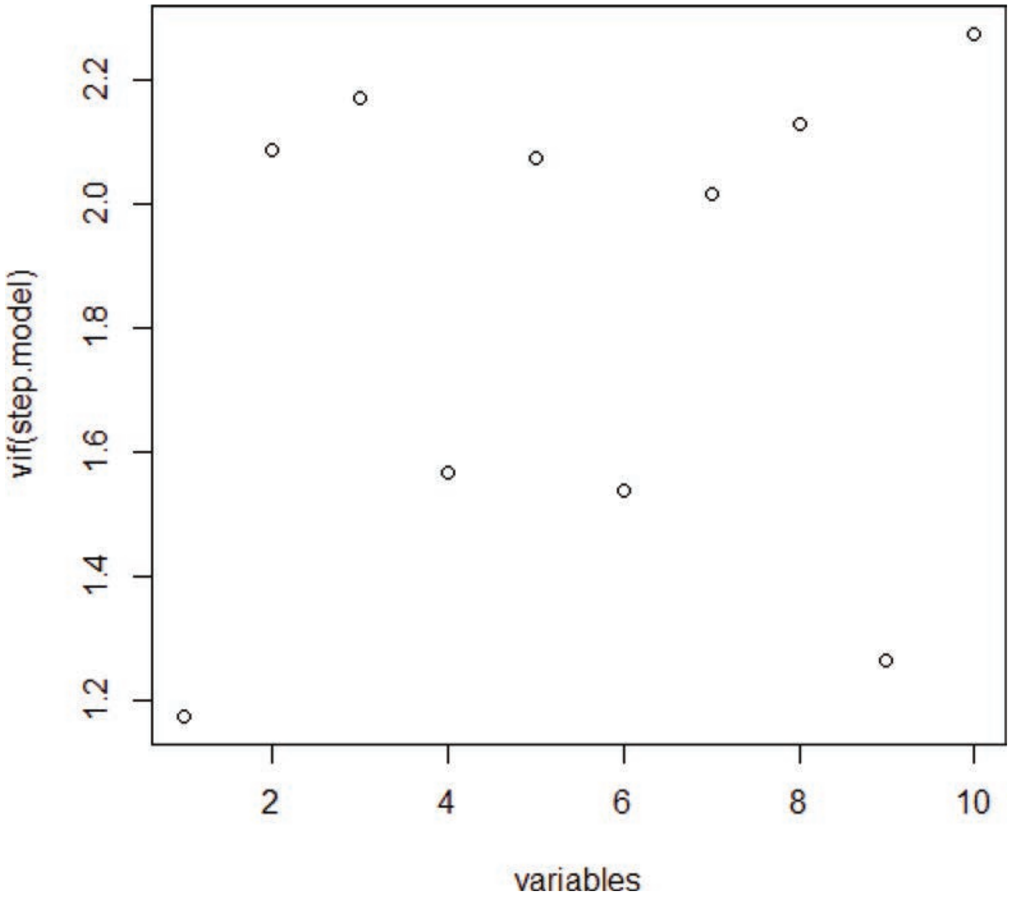

Figure 2 Variance inflation factor for stepwise model.

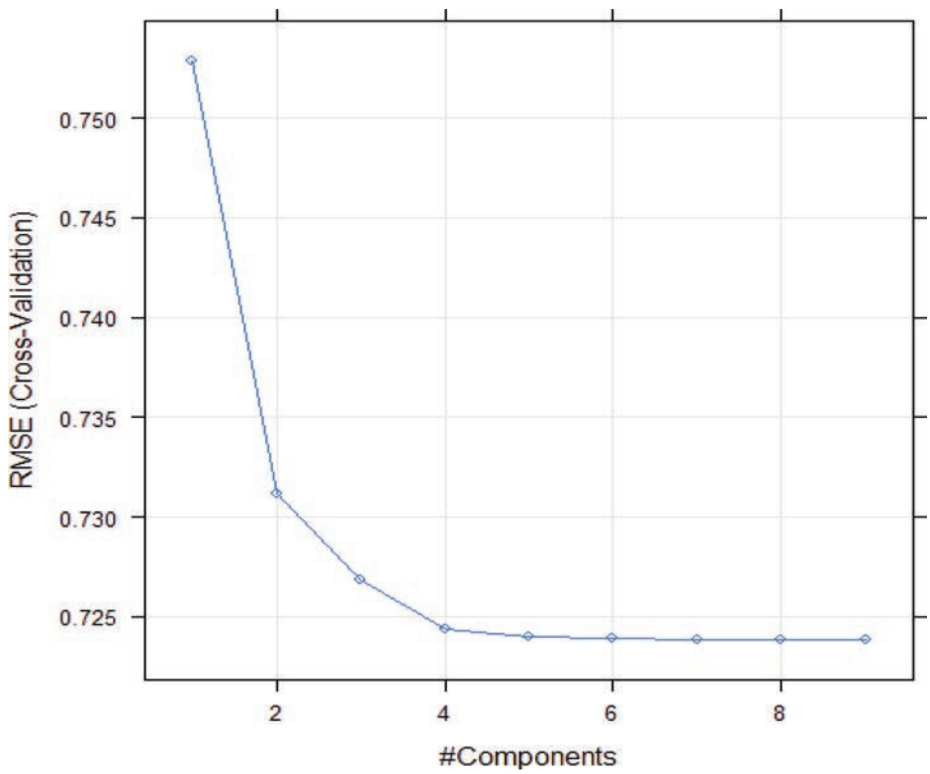

Figure 3 Cross-validation with PLS results for Equation.

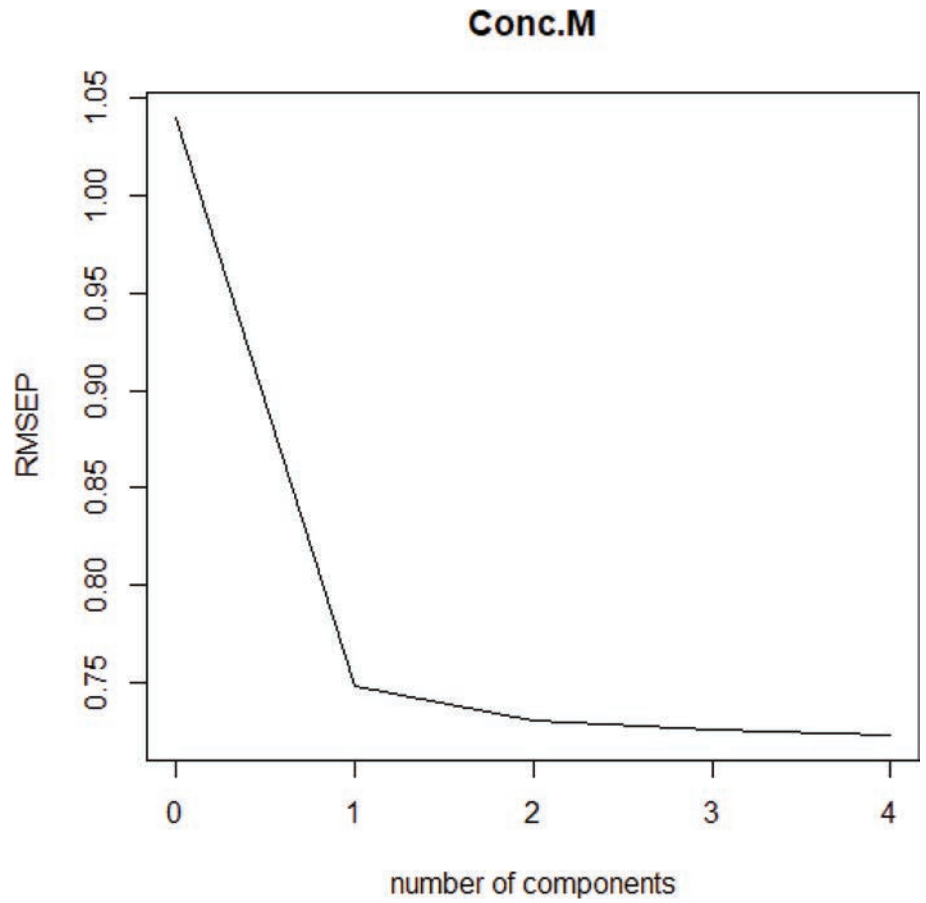

Figure 4 Prediction PLS results using four components.

After precise scrutiny of the prediction power of the built model for unseen data, we usually split the dataset randomly such that 80 percent of them constitute the training words, and the rest are categorised as test words. Then, 10-fold cross-validation with Partial Least Square (PLS) analysis results, as illustrated in Fig. 3, revealed that our best model should be used with only four components to predict the unseen test data. After this four-component threshold, the prediction error remains stable, as demonstrated in the plot. This finding underscores the efficiency of our model in capturing the essential features required for accurate predictions, while further components do not significantly contribute to enhancing its performance.

Thereby, the prediction of the test dataset was conducted by random selection of 20 percent of the entire dataset. The results with PLS presented in Fig. 4 for RMSE = 0.7225 and R-square of 0.5173 showed the acceptable quality of our model for the prediction of new test data.

Discussion

Sensorimotor data holds significant importance in understanding cognition. Existing studies that explore sensorimotor word meanings and concepts have often been limited by small sample sizes and a narrow range of sensorimotor experiences. However, the Lancaster norms provide a substantial dataset encompassing sensorimotor strength for 39,707 concepts across six perceptual modalities (touch, hearing, smell, taste, vision, and interoception) and five action effectors (mouth/throat, hand/arm, foot/leg, head excluding mouth/throat, and torso). This data was collected from 3,500 Amazon Mechanical Turk participants.

The current study delved deeper into the dataset to determine which sensory-motor or modality-specific norms from the Lancaster dataset are most pertinent to predicting concreteness. Distinguishing between concreteness and abstractness is a well-known challenge in this field, as reviewed by Montefinese in 2019. Moreover, the application of these norms in the detection of properties in unpredicted and new pseudo-words is a burgeoning area of research, as indicated by Chuang et al. in 2020.

Through a rigorous statistical selection process, eight variables have been identified within the analysis. These variables yielded six significant components for predicting concreteness values in the Brysbaer dataset. Regression coefficients are pivotal in estimating unknown population parameters and characterizing the relationship between predictors and responses in linear regression.

Among these coefficients, the three highest in our Stepwise Multiple Linear Regression (SW-MLR) model were visual mean (strength), haptic power, and interceptive strength, with values of 0.33(±0.005), 0.294(±0.005), and –0.35(±0.005), respectively. These parameters reflect how participants experienced words through visual perception, haptic, and introspective modalities. It's noteworthy that previous studies have not consistently linked object properties with tactile information, suggesting that tactile limitations for linguistic stimuli could result from an evolutionary adaptation related to endogenous attention (Connell & Lynott, 2010).

In contrast to haptic or visual perception, introspective perception (interoception) exhibited a negative correlation with concreteness. This underscores the relative significance of interoceptive perception in representing abstract concepts. Interoception involves perceiving sensations originating from within the body, encompassing physical sensations related to internal organ functions, such as heartbeat and respiration, as well as autonomic nervous system activity related to emotions (Zmigrod & Hommel, 2013). This understanding could be pertinent to conditions like schizophrenia, where disrupted interoception might play a role in various cognitive and emotional symptoms.

This study also considered olfactory perception, a process that begins with the stimulation of olfactory sensory neurons and results in conscious awareness of an odor. We found a direct relationship between concreteness and both olfactory and torso strengths, with average regression coefficients near 0.2 (±0.008). This suggests that items stimulating olfaction or involving the torso region of the body tend to be more concrete than abstract.

In our analysis, auditory, head, and foot-leg strengths exhibited the lowest regression coefficients, all with negative signs, while gustatory and hand-arm modalities showed positive signs. Notably, our best model, Eq. (1), did not include the head-mouth variable after the stepwise variable selection process, indicating its limited predictive power for concreteness ratios.

Auditory perception also played a role in our study, with most individuals losing the ability to hear higher frequencies as they age. Human hearing typically falls within the range of 20 Hz to 20 kHz, with the ear being most sensitive to frequencies between 1000 and 3,500 Hz, which aligns with the frequency range of human speech communication (Kohansal, 2023). However, these properties may vary among individuals, such as introverts and extroverts, although specific sample statistics were not available in the current dataset.

Conclusion

Concreteness and abstractness of words and non-words are fuzzy and graded properties. Classical properties can be considered the basis for fuzzy properties, an extension and significant simplification of classical properties. It is easiest to comprehend within the framework of one's participation in a set.

In essence, it permits partial membership, indicating that it contains components with variable degrees of membership in the properties. Here, we applied a stepwise linear regression method to select the best model for predicting the concreteness value in the Brysbaer dataset using Lancaster English frequent word norms.

Indeed, the step-by-step construction of a regression model in stepwise regression involves selecting independent variables to construct a final model. This method adds or removes potential explanatory variables in succession, and statistical significance is tested after each iteration (van Rooij, 2021). Consequently, we found that all 11 variables of this dataset except the Head-mouth parameter are valuable predictors.

As a new demand to know the concreteness values of non-words and infrequent words, our statistical method can pave the way for controlled experiments when choosing words as a stimulus is critical. One limitation of our study was the same orthographical dataset which is a simplified understanding of concrete and abstract words. Recent studies show a correlation between orthography and concreteness (Posner, 2022). Future observational studies can prove the validity of our computational model combined with the advanced orthographical dataset for the prediction of the concreteness of infrequent and non-words.

Data Availability

The datasets generated and/or analyzed throughout the current study are available from the corresponding author, which can be made available at a reasonable request.

Conflicts of Interest

There is no conflict of interest.

Ethical Statement

The ethical statement does not apply to this study.

Informed Consent

Not Applicable

References

Alin, A. (2010). Multicollinearity. *Wiley Interdisciplinary Reviews: Computational Statistics, 2*(3), 370–374.

Allen, M., Levy, A., Parr, T., & Friston, K. J. (2019). In the body's eye: The computational anatomy of interoceptive inference. *bioRxiv.* Article 603928.

Aiken, L. S., West, S. G., & Pitts, S. C. (2003). Multiple linear regression. I. B. Weiner (Ed.), *Handbook of Psychology* (pp. 481–507). John Wiley & Sons. https://doi.org/10.1002/0471264385.wei0219

Andreasen, N. C. (1979). Thought, language, and communication disorders: I. Clinical assessment, definition of terms, and evaluation of their reliability. *Archives of General Psychiatry, 36*(12), 1315–1321.

Barber, H. A., Otten, L. J., Kousta, S. T., & Vigliocco, G. (2013). Concreteness in word processing: ERP and behavioral effects in a lexical decision task. *Brain and Language, 125*(1), 47–53.

Barsalou, L. W. (1999). Perceptions of perceptual symbols. *Behavioral and Brain Sciences, 22*(4), 637–660.

Barsalou, L. W. (2008). Grounded cognition. *Annual Review of Psychology, 59,* 617–645. https://doi.org/10.1146/annurev.psych.59.103006.093639

Barsalou, L. W., Simmons, W. K., Barbey, A. K., & Wilson, C. D. (2003). Grounding conceptual knowledge in modality-specific systems. *Trends in Cognitive Sciences, 7*(2), 84–91.

Baumann, K. (2003). Cross-validation as the objective function for variable-selection techniques. *TrAC Trends in Analytical Chemistry, 22*(6), 395–406.

Belt, E. S., & Lowenthal, P. R. (2021). Video use in online and blended courses: A qualitative synthesis. *Distance Education, 42*(3), 410–440.

Benedetto, L., Cremonesi, P., Caines, A., Buttery, P., Cappelli, A., Giussani, A., & Turrin, R. (2023). A survey on recent approaches to question difficulty estimation from text. *ACM Computing Surveys, 55*(9), 1–37.

Bhardwaj, S., Rana, G. A., Behl, A., & de Caceres, S. J. G. (2023). Exploring the boundaries of Neuromarketing through systematic investigation. *Journal of Business Research, 154,* 113371.

Brysbaert, M., Warriner, A. B., & Kuperman, V. (2014). Concreteness ratings for 40 thousand generally known English word lemmas. *Behavior Research Methods, 46*(3), 904–911.

Connell, L. (2019). What have labels ever done for us? The linguistic shortcut in conceptual processing. *Language, Cognition and Neuroscience, 34,* 1308–1318.

Connell, L., & Lynott, D. (2010). Look but don't touch: Tactile disadvantage in processing modality-specific words. *Cognition, 115*(1), 1–9.

Connell, L., & Lynott, D. (2014b). Principles of representation: Why you can't represent the same concept twice. *Topics in Cognitive Science, 6,* 390–406.

Dohoo, I., Ducrot, C., Fourichon, C., Donald, A., & Hurnik, D. (1997). An overview of techniques for dealing with large numbers of independent variables in epidemiologic studies. *Preventive Veterinary Medicine, 29*(3), 221–239.

Dolatabadi, M., Nekoei, M., & Banaei, A. (2010). Prediction of antibacterial activity of pleuromutilin derivatives by genetic algorithm–multiple linear regression (GA–MLR). *Monatshefte für Chemie-Chemical Monthly, 141,* 577–588.

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., ... & Lautenbach, S. (2013). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography, 36*(1), 27–46.

Faden, J., & Citrome, L. (2023). Schizophrenia: One name, many different manifestations. *Medical Clinics, 107*(1), 61–72.

Fernandes, A. M., & Albuquerque, P. B. (2012). Tactual perception: A review of experimental variables and procedures. *Cognitive Processing, 13,* 285–301.

Fetterman, A. K., Bair, J. L., Werth, M., Landkammer, F., & Robinson, M. D. (2016). The scope and consequences of metaphoric thinking: Using individual differences in metaphor usage to understand how metaphor functions. *Journal of Personality and Social Psychology, 110*(3), 458–476. https://doi.org/10.1037/pspp0000067

Gibbs, R. W. (2017). *Metaphor wars*. Cambridge University Press.

Grinter, E. J., Maybery, M. T., & Badcock, D. R. (2010). Vision in developmental disorders: is there a dorsal stream deficit? *Brain Research Bulletin, 82*(3–4), 147–160.

Heinze, G., Wallisch, C., & Dunkler, D. (2018). Variable selection–a review and recommendations for the practicing statistician. *Biometrical journal, 60*(3), 431–449.

Hellmann, J. H., Echterhoff, G., & Thoben, D. F. (2013). Metaphor in embodied cognition is more than just combining two related concepts: A comment on Wilson and Golonka (2013). *Frontiers in Psychology, 4,* 201. https://doi.org/10.3389/fpsyg.2013.00201

Hill, F., Korhonen, A., & Bentz, C. (2014). A quantitative empirical analysis of the abstract/concrete distinction. *Cognitive Science, 38*(1), 162–177.

Hodel, A., Olszewska, J., & Falkowski, A. (2022). With concreteness details fade: Dissociative effect of labelling of concrete and abstract stimuli on memory. *Journal of Cognitive Psychology, 34*(2), 217–242. https://doi.org/10.1080/20445911.2021.2018446

Hoffman, P., & Lambon Ralph, M. A. (2011). Reverse concreteness effects are not a typical feature of semantic dementia: Evidence for the hub-and-spoke model of conceptual representation. *Cerebral Cortex, 21*(9), 2103–2112. https://doi.org/10.1093/cercor/bhq288

Jiang, Y., & Punj, G. N. (2010). The effects of attribute concreteness and prominence on selective processing, choice, and search experience. *Journal of the Academy of Marketing Science, 38*(4), 471–489.

Kohansal, B., Asghari, M., & Habibi, M. (2023). The occupational noise-induced tinnitus: A review of auditory behavioral and electrophysiological evaluations. *Auditory and Vestibular Research, 32*(2), 81–89.

Krahmer, E., & Stapel, D. (2009). Abstract language, global perception: How language shapes what we see. In *Proceedings of the Annual Meeting of the Cognitive Science Society, 31,* 286–291.

Li, B., Wang, Y., Wang, K., & Zhang, D. (2023). A review of data-driven techniques for neuromarketing. *Advanced Manufacturing and Automation, XII,* 748–755.

Lim, F. V. (2021). Designing learning with embodied teaching: Perspectives from multimodality. Routledge.

Lodico, M. G., Spaulding, D. T., & Voegtle, K. H. (2010). *Methods in educational research: From theory to practice* (2nd ed.). John Wiley & Sons.

Lynott, D., Connell, L., Brysbaert, M., Brand, J., & Carney, J. (2019). The Lancaster Sensorimotor Norms: Multidimensional measures of perceptual and action strength for 40,000 English words. *Behavior Research Methods, 52*(3), 1271–1291. https://doi.org/10.3758/s13428-019-01316-z

McCutcheon, R. A., Keefe, R. S., & McGuire, P. K. (2023). Cognitive impairment in schizophrenia: Aetiology, pathophysiology, and treatment. *Molecular Psychiatry, 28,* 1902–1918. https://doi.org/10.1038/s41380-023-01949-9

Modesti, M. N., Arena, J. F., Palermo, N., & Del Casale, A. (2023). A Systematic Review on Add-On Psychotherapy in Schizophrenia Spectrum Disorders. *Journal of Clinical Medicine, 12*(3), 1021.

Montefinese, M. (2019). Semantic representation of abstract and concrete words: A minireview of neural evidence. *Journal of Neurophysiology, 121*(5), 1585–1587.

Nekoei, M., Salimi, M., Dolatabadi, M., & Mohammadhosseini, M. (2011). Prediction of antileukemia activity of berbamine derivatives by genetic algorithm–multiple linear regression. *Monatshefte für Chemie-Chemical Monthly, 142,* 943–948.

Panicheva, P. V., Mamaev, I. D., & Litvinova, T. A. (2023). Towards automatic conceptual metaphor detection for psychological tasks. *Information Processing & Management, 60*(2), 103191.

Peng, M., Zhang, L., Yiran, W., & Qingbai, Z. (2020). Internet-word compared with daily-word priming reduces attentional scope. *Experimental Brain Research, 238*(4), 1025–1033.

Pezzulo, G. (2014). Why do you fear the bogeyman? An embodied predictive coding model of perceptual inference. *Cognitive, Affective, & Behavioral Neuroscience, 14*, 902–911.

Pi, Z., Zhu, F., Zhang, Y., Chen, L., & Yang, J. (2022). Complexity of visual learning material moderates the effects of instructor's beat gestures and head nods in video lectures. *Learning and Instruction, 77,* 101520.

Posner, J. L. (2022). It sounds the way it's spelled: Orthography effect mechanisms in persons with aphasia. (Doctoral dissertation, Georgetown University).

Smith, L., & Gasser, M. (2005). The development of embodied cognition: Six lessons from babies. *Artificial Life, 11*, 13–29.

Stelmack, R. M., & Campbell, K. B. (1974). Extraversion and auditory sensitivity to high and low frequency. *Perceptual and Motor Skills, 38*(3), 875–879.

Stephan, K. E., Manjaly, Z. M., Mathys, C. D., Weber, L. A., Paliwal, S., Gard, T., Tittgemeyer, M., Fleming, S. M., Haker, H., Seth, A. K., & Petzschner, F. H. (2016). Allostatic self-efficacy: A metacognitive theory of dyshomeostasis-induced fatigue and depression. *Frontiers in Human Neuroscience, 10,* 550. https://doi.org/10.3389/fnhum.2016.00550

Stull, A. T., Fiorella, L., & Mayer, R. E. (2021). The case for embodied instruction: The instructor as a source of attentional and social cues in video lectures. *Journal of Educational Psychology, 113*(7), 1441.

Suárez, M. D. M. (2022). The identification of learner profiles and the role of sound-symbol correspondence. In Comunicació a: ICEL 2022-3rd International Conference on Education and Linguistics. May 12, 2022. Westminster International University in Tashkent (Online).

van Rooij, I., & Baggio, G. (2021). Theory before the test: How to build high-verisimilitude explanatory theories in psychological science. *Perspectives on Psychological Science, 16*(4), 682–697.

Vigliocco, G., Kousta, S.-T., Della Rosa, P. A., Vinson, D. P., Tettamanti, M., Devlin, J. T., & Cappa, S. F. (2014). The neural representation of abstract words: The role of emotion. *Cerebral Cortex, 24*(7), 1767–1777. https://doi.org/10.1093/cercor/bht025

Vigliocco, G., Meteyard, L., Andrews, M., & Kousta, S. (2009). Toward a theory of semantic representation. *Language and Cognition, 1,* 219–247.

Wang J., Conder J.A., Blitzer D.N., Shinkareva S.V. (2010). Neural representation of abstract and concrete concepts: A meta-analysis of neuroimaging studies. *Human Brain Mapping, 31*, 1459–1468. https://doi.org/10.1002/hbm.20950

Wilson, M. (2002). Six views of embodied cognition. *Psychonomic Bulletin & Review, 9,* 625–636.

Yao, Y., & Zheng, X. (2020). Book review: Embodied cognition. *Frontiers in Psychology, 11,* 42. https://doi.org/10.3389/fpsyg.2020.00042

Zapparrata, N. M., Brooks, P. J., & Ober, T. (2023). Developmental language disorder is associated with slower processing across domains: A meta-analysis of time-based tasks. *Journal of Speech, Language, and Hearing Research*. Advance online publication. https://doi.org/10.1044/2022_JSLHR-22-00221

Zmigrod, S., & Hommel, B. (2013). Feature integration across multimodal perception and action: A review. *Multisensory Research, 26*(1–2), 143–157. https://doi.org/10.1163/22134808-00002390