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Spiky Anger, Round Peace: Examining Valence, Arousal, and Linguistic Associations in Emotion-Eliciting Concepts

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Abstract

This research examines how valence, arousal, and linguistic co-occurrence patterns influence shape-emotion associations. Across three studies, we tested whether positive and negative words are associated with rounded and sharp shapes, respectively, and whether a semantic analysis of language (*Word2Vec*) can predict these associations. Studies 1A and 1B focused primarily on valence, using a lexical decision task and a rating task. Both studies found that positive words were associated with rounded shapes and negative words with sharp shapes, with *Word2Vec* successfully predicting these mappings. Study 2 directly manipulated both valence and arousal, revealing that when arousal became a salient factor, it dominated shape-emotion associations: low-arousal words were reliably associated with rounded shapes, whereas high-arousal words showed no consistent shape association. Additionally, *Word2Vec*'s predictive power weakened when arousal was varied, suggesting that valence is more systematically encoded in linguistic representations, while arousal effects may depend more on the flexible, situated dynamics of emotional experience. Together, these findings suggest that while valence-based shape-emotion associations are stable under moderate arousal, salient arousal can shift conceptual mappings. These results highlight the joint contributions of linguistic and perceptual systems to emotional meaning and offer new insights into the grounding of emotion concepts.

Keywords: shape-emotion associations, valence, arousal, linguistic distributional models, language and perception

Introduction

Understanding how humans represent conceptual knowledge is a central question in cognitive science research. There is now a wealth of evidence suggesting that conceptual knowledge is distributed across multiple systems rather than any specific single system (e.g., embodied or symbolic, e.g., Borghi et al., 2017; Dove, 2009). The contribution of these systems appears to vary with the type of concept: while concrete concepts (e.g., car, sofa) rely more heavily on perceptual features (e.g., Horchak & Garrido, 2022, 2024), abstract concepts (e.g., passion, danger) are often grounded in emotional states and linguistic associations (e.g., Barsalou & Wiemer-Hastings, 2005).

Supporting this view, studies have shown that abstract words typically carry stronger affective associations than concrete words, with valence (positive-negative affect) and arousal (emotional intensity) emerging as key dimensions of their representation (Kousta et al., 2011; Vigliocco et al., 2009). These findings align with embodied cognition theories, which emphasize grounding in sensorimotor and emotional systems (Niedenthal, 2007; Solomon & Barsalou, 2001). However, others argue that emotional embodiment captures only a subset of abstract concepts, and that linguistic structure plays a dominant role (Borghi et al., 2017; Winter, 2022).

Indeed, linguistic experience appears crucial for abstract meaning. Reaction times for abstract concepts are predicted better by linguistic features (e.g., contextual dispersion, semantic neighbors) than by perceptual features (e.g., Recchia & Jones, 2012), and neuroimaging studies have found that abstract concepts activate left-hemisphere language-related areas (Wang et al., 2010). Together, these findings highlight the important contributions of emotional experience and linguistic co-occurrence patterns to conceptual representation.

The Role of Emotion: Valence, Arousal, and Linguistic Regularities

Research suggests that both valence and arousal can be partially predicted from linguistic co-occurrence patterns, but with important differences. Valence appears systematically encoded in language, as shown by Recchia and Louwerse (2015), who found strong correlations between word co-occurrence statistics and human affective ratings. In contrast, arousal showed weaker and more variable predictability, hinting that emotional intensity may rely more on embodied and contextual factors (Kuperman et al., 2014).

This distinction becomes even more apparent in everyday language: while it is easy to determine that words like *joy* and *pain* convey positive and negative valence, it is harder to say which of these two words carries greater arousal. Consequently, it is reasonable to assume that arousal often depends on situational context than lexical distribution alone.

Yet, even without considering linguistic regularities, the available empirical evidence suggests that the relationship between valence and arousal is more complex than one might expect. As one example, a meta-analysis by Ferré et al. (2024) revealed that while positive valence reliably facilitates word recognition, the effects of negative valence are inconsistent and depend on arousal and context. As a different example, Yik et al. (2023) conducted large-scale cross-cultural research, challenging popular models of valence-arousal interactions. While many theories assume that arousal increases symmetrically for both positive and negative emotions (e.g., Russell, 1980), their study revealed that arousal increased only with positive emotions but not with negative ones. Furthermore, valence only weakly predicted arousal, thus aligning with some prior research showing that the effects of valence and arousal on word recognition are often independent, not interactive (Kuperman et al., 2014).

Beyond these empirical findings, theoretical models suggest that arousal may directly shape perceptual and attentional processing in ways relevant to conceptual representation. For example, the "weapon-focus effect" (see Steblay, 1992, for a review) from memory research shows that high arousal narrows attention toward salient stimuli (e.g., a weapon) while suppressing processing of peripheral details (e.g., information about a killer). Similarly, the Yerkes-Dodson Law (Yerkes & Dodson, 1908) posits that high arousal can impair cognitive performance by narrowing attentional scope. Applied to language comprehension, these findings suggest that high emotional intensity may cause individuals to prioritize core emotional content while downplaying peripheral features like visual shape.

This perspective may help explain why words of similar valence can evoke different shape associations depending on their arousal level. For instance, while the word "spirit" typically relates to a sense of vitality (or unity) and has a more serious undertone, the word "fun" is usually associated with enjoyment or lightheartedness, emphasizing a more carefree aspect of positive experiences. Both are positively valenced, but they represent different shades of positivity. More specifically, "spirit" denotes connection and wholeness, which may be associated with the smoothness of rounded shapes. In contrast, "fun" emphasizes excitement, which might not evoke as strong a connection to rounded shapes. Consequently, the association of "spirit" with roundness could be stronger than the association of "fun" with roundness. Likewise, negatively valenced words such as "loneliness" and "danger" evoke different emotional tones. "Loneliness" is typically associated with feelings of isolation and sadness – low-arousal experiences that might metaphorically correspond to empty or enclosed spaces and thus should be more intuitively linked to round shapes. In contrast, "danger" is a high-arousal negative word that conveys immediate threat and urgency. Because of this heightened arousal,

"danger" is much more likely to be associated with spiky shapes, which visually mirror the intensity and sharpness of the emotion it evokes. Therefore, even when words have the same valence, they can give rise to different associations with visual shapes, depending on their specific connotations.

Together, these empirical findings and theoretical considerations suggest that arousal may independently influence emotion–shape associations during conceptual processing. However, the extent to which arousal shapes associations with visual features remains unclear.

Beyond Valence and Arousal: The Role of Emotion-Shape Associations

One promising avenue for addressing this question involves examining how emotional properties map onto visual shape. Previous studies showed consistent associations between angular shapes and negative emotions and between rounded shapes and positive emotions (e.g., Bar & Neta, 2006). However, growing evidence suggests that arousal also plays a major role. For example, Aryani et al. (2018) showed that high-arousal words tend to have abrupt phonetic features linked to angular shapes, whereas low-arousal words feature softer sounds associated with roundness. Sievers et al. (2019) similarly found that spiky shapes are linked to high-arousal emotions, while rounded shapes align with low-arousal emotions, independent of valence.

These findings align with research on sound symbolism, where phonemes systematically map onto sensory properties such as shape. Much of the classical research in this area has focused on nonwords, with one of the most famous phenomena being the *bouba/kiki effect* (Köhler, 1929; Ramachandran & Hubbard, 2001) when participants associate words like "bouba" with rounded shapes and "kiki" with spiky shapes, thus suggesting a systematic mapping between language sounds and visual properties.

Although the *bouba/kiki* effect is often considered a classic example of sound-shape correspondences, these associations clearly extend beyond phonetic features into emotional and perceptual dimensions. More specifically, speech sounds associated with specific shapes also systematically co-occur with certain emotional characteristics. For instance, phonemes linked to rounded shapes (e.g., /o/) tend to appear in pseudowords denoting softness, smoothness, and low arousal, whereas phonemes associated with sharp shapes (e.g., /k/) frequently occur in pseudowords describing sharpness, roughness, and high arousal (Aryani et al., 2020; Sidhu & Pexman, 2022). Consequently, both shape and sound encode affective meaning.

Although much work on sound symbolism has focused on nonwords, empirical evidence suggests that crossmodal iconicity (i.e., where the sound of a word corresponds to a property in a different sensory modality, such as shape) extends to real words (see Sidhu, 2025, for a recent review). Examining real words is particularly important because it provides a more ecologically valid test of phonetic-emotional correspondences in everyday language use. After all, in real language, sound-symbolic effects could be affected by lexical familiarity, communicative intent, or sociocultural characteristics. Considering this, real words offer a meaningful avenue for exploring crossmodal associations, making them the focus of the present research.

Several studies provide strong support for phonetic-emotional mappings in real language. Calvillo-Torres et al. (2024) conducted a large-scale phoneme-affect analysis of Spanish words, testing whether specific sounds predict emotional properties. Their findings revealed that voiceless (/p/, /t/) and voiced (/β/, /d/, /g/) plosives were more frequent in high-arousal words in general. In contrast, sibilant fricatives (/s/, /z/, /θ/) and non-sibilant fricatives (/f/) were particularly overrepresented in high-arousal negative words, including those expressing fear, anger, and disgust. Similarly, Westbury (2005) investigated phoneme-shape congruency by

conducting a lexical decision task in which participants classified words and nonwords embedded within spiky or curvy frames. The results showed that spiky frames slowed responses to words containing continuant consonants (e.g., “moon”), while curvy frames interfered with words containing plosives (e.g., “toad”). Together, these findings suggest that phonological and visual features interact during lexical processing.

Further evidence for shape-emotion correspondences comes from Palumbo et al. (2015), who used an Implicit Association Test to show that round shapes were linked to low-arousal, positive concepts (e.g., comfort), while angular shapes were associated with high-arousal, negative concepts (e.g., danger). However, because they used different word sets for valence and arousal across experiments, it remains unclear how valence and arousal jointly influence responses to the same stimuli.

Moreover, not all studies find consistent crossmodal effects in real-word processing. For example, Sidhu and Pexman (2022) found no size-sound symbolism effect in a size judgment task, suggesting that phoneme-size mappings are moderated by semantic context and lexical familiarity. Similarly, Sučević et al. (2013) showed that frame-shape congruence effects in lexical decision tasks depended on timing: congruence effects emerged only when frames and words appeared simultaneously and were short-lived when frames preceded words by over a second.

Altogether, while shape-emotion links are evident, their reliability across different linguistic contexts and temporal conditions remains uncertain.

Remaining Questions and the Present Research

Given these mixed findings, key questions remain regarding whether crossmodal emotion–shape associations generalize to abstract words – concepts referring to social, emotional, or

introspective content (Barsalou & Wiemer-Hastings, 2005). A second unresolved issue concerns the respective roles of valence and arousal: while angular shapes are typically linked to negative emotions and rounded shapes to positive ones, arousal may exert an even stronger influence (Sievers et al., 2019). Finally, although prior studies have explored phoneme–emotion links in real words (e.g., Sidhu & Pexman, 2022), their contribution to emotion–shape associations remain underspecified for abstract words.

To address these questions, the present research examined whether shape–emotion associations extend to abstract concepts and how valence and arousal interact in shaping such associations. Importantly, we complemented behavioral measures with predictions from *Word2Vec*, a computational model of linguistic co-occurrence (Mikolov et al., 2013). Across three studies, we combined implicit (lexical decision) and explicit (shape rating) tasks to evaluate perceptual and linguistic contributions to emotion–shape mappings. This design extends previous work by explicitly modeling arousal, incorporating distributional semantic predictions, and using both implicit and explicit tasks to assess abstract words.

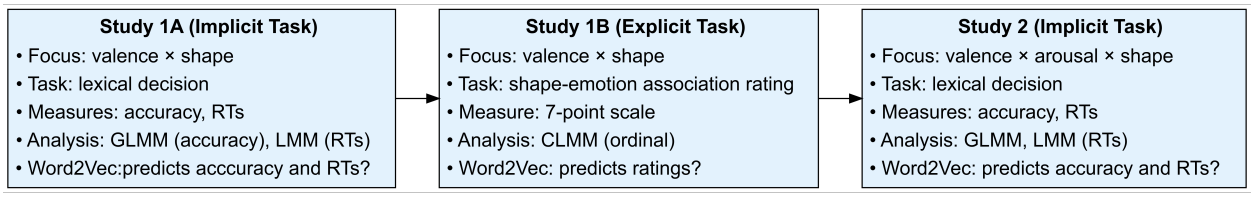
Overview of the Present Research

To address these issues, we conducted three studies designed to shed light on the role of valence, arousal, and linguistic distributional patterns in shape-emotion associations (see Figure 1). In Study 1A, participants performed an implicit lexical decision task, deciding whether letter strings embedded in shape-congruent or incongruent frames were real words. In Study 1B, participants explicitly rated the degree to which each word was associated with a visual shape (e.g., “anger” → spiky; “peace” → round). In both studies, we focused primarily on valence while keeping arousal levels approximately moderate.

In Study 2, we extended this investigation by using the same lexical decision task but directly disentangling valence and arousal effects. By systematically varying stimuli across high/low valence and high/low arousal conditions, we assessed whether shape-emotion mappings are primarily driven by valence, arousal, or their interaction. Additionally, across all experiments, we collected *Word2Vec* similarity scores measuring the association between each word and shape-related terms (e.g., "round," "sharp") to examine whether linguistic co-occurrence patterns, visual features, or both better explain shape-emotion associations.

Figure 1

Overview of the Three Studies: Tasks, Measures, and Analyses



Note. GLMM = Generalized Linear Mixed-Effects Model (used for analyzing accuracy); LMM = Linear Mixed-Effects Model (used for analyzing response times); CLMM = Cumulative Link Mixed Model (used for analyzing ratings).

Hypotheses

We predicted that if emotion-eliciting words are grounded in visual shape, participants would associate positive words with round shapes and negative words with sharp shapes, particularly when arousal remains moderate (Studies 1A and 1B). If this association is encoded in language, *Word2Vec* should also predict higher similarity scores for "positive-round" and "negative-sharp" pairs than for mismatched pairs.

We had two competing hypotheses regarding the effect of arousal on participants' responses. Our first prediction was that positive stimuli would be more strongly associated with round

shapes when arousal is moderate rather than high, whereas negative stimuli would be more strongly associated with spiky shapes when arousal is high rather than moderate. Alternatively, based on cognitive models of attentional narrowing mentioned before (e.g., Steblay, 1992; Yerkes & Dodson, 1908), high arousal could disrupt these shape–emotion correspondences, weakening associations as emotional intensity increases.

Study 1A

In Study 1A, we tested whether visual shape is automatically activated during the recognition of abstract words. Using a lexical decision task, we examined whether response times were influenced by the congruence between a word's emotional valence and the shape of its presentation frame. We predicted faster responses for positively valenced words in round frames and negatively valenced words in sharp frames. Additionally, we explored whether arousal and *Word2Vec* similarity scores contributed to these associations.

Method

Data Processing and Ethics

Data cleaning, statistical analysis, and data visualization were conducted using R (R Core Team, 2020). All procedures abided by the World Medical Association's Declaration of Helsinki and the ethical guidelines of the host institution. The research was approved by the host institution's ethics committee (approval number 24/073).

Power Analysis

We performed a simulation-based power analysis ("mixedpower" R package of Kumle et al., 2021) to estimate the sample size required to detect our primary effect of interest: the interaction between word valence/arousal and visual shape. As no directly comparable study was available, we based our estimate on a related lexical decision study by Yao et al. (2022), which reported a

significant interaction between semantic size and font size. Although semantic size represents a relatively concrete dimension, potentially grounded more heavily in perceptual features, we selected this study as a benchmark primarily due to its methodological similarity – both studies employ a lexical decision task and test interaction effects using mixed-effects models. To address potential conceptual differences between semantic size and emotional valence/arousal, we implemented two precautionary strategies to reduce the risk of Type I errors: (a) setting a higher power threshold of 90% (instead of the conventional 80%) and (b) defining a smallest effect size of interest (SESOI) by reducing fixed-effect estimates by 15%, following Kumle et al. (2021). Incorporating these adjustments, simulation results suggested that 60 to 80 participants would be required to achieve 90-95% power to detect the expected interaction. Based on this estimate, we aimed to recruit at least 80 participants for each study[1].

Participants

Eighty-two native Portuguese students participated in Study 1A. As the data from one participant had to be discarded due to an unusually low accuracy (<45%), the results are based on the data from 81 participants (M_{age} = 20.81, SD_{age} = 2.62; 65 females). Participants received course credit for their participation and provided informed consent prior to the study.

Design and Materials

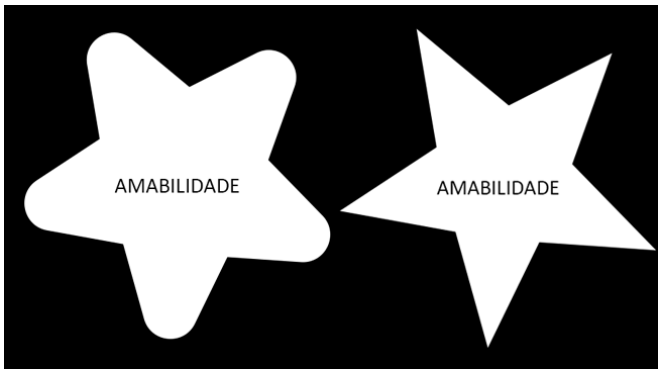
Study 1A employed a 2 (valence: positive vs. negative) x 2 (shape: sharp vs. round) within-participants design. It comprised 128 stimuli (64 words and 64 nonwords). Words were selected from the adaptation of the ANEW database (Bradley & Lang, 1999) for European Portuguese (Soares et al., 2012). Across valence levels, words were approximately matched item-by-item for length (number of letters) and frequency (log occurrences per million), with frequency data drawn from SUBTLEX-PT (Soares et al., 2015).

As the study primarily focused on valence, words were selected to maximize differences in positive and negative affect. However, arousal was statistically controlled by including it as a predictor in the analysis, using each item's arousal score from the Soares et al. (2012) database. Abstractness was operationalized using Brysbaert et al.'s (2014) concreteness database, where ratings of 4 – 5 indicate concrete (experience-based) concepts and lower ratings (from 1 to 3) correspond to abstract concepts. The selected words had a mean concreteness rating of 2.66. All major specifications for words are provided in Appendix 1.

To determine the role of linguistic processing in predicting the association between word valence and visual shape, we performed a word embedding analysis with a *Word2Vec* model (Mikolov et al., 2013) using the University of Colorado's website (*http://wordvec.colorado.edu/index.html*). Specifically, we paired the words "sharp" and "round" with each of the 64 positively- and negatively-valenced words[2]. If linguistic structure encodes shape-emotion associations, matching pairs (e.g., round–peace) should show greater similarity than mismatched pairs (e.g., sharp–peace)[3].

Figure 2

An Example of a Visual Display with Target Stimuli in Study 1a.



Note. English translation for the words inside the figures: AMABILIDADE = KINDNESS.

Additionally, 20 frame pairs (e.g., triangles, pentagons) were created. Frames had a white background, equal number of corners, and nearly identical sizes, differing only in whether corners were sharp or rounded. Words and nonwords were placed at the center of these frames, with both word and frame presented simultaneously against a black background (see Figure 2). Two stimulus lists were used: in each, half the words in each condition appeared in round frames and half in sharp frames, with frame assignment reversed across lists.

Procedure

Stimuli were presented online using PsyToolkit (Stoet, 2010, 2017). Participants saw a series of letter strings and had to decide as quickly and accurately as possible whether each item was a real word or a nonword using the "L" or the "A" key, respectively. They were informed that the words would be displayed inside different frames to investigate the influence of visual information on attention.

Before the actual experiment, participants completed ten practice trials with visual feedback on their response accuracy. In the experimental phase, each trial began with a fixation cross presented for 1000 milliseconds, followed by a blank screen for 500 milliseconds, and then by the centrally displayed frame containing the word or nonword. The stimulus remained on the screen until a response was made or 3000 milliseconds elapsed. Failure to respond within the time window triggered a feedback message ("INCORRECT RESPONSE" or "TOO SLOW") displayed for 1500 milliseconds before the next trial. Trial order was randomized.

Results

Data Analysis Strategy

We analyzed both accuracy and response times (RTs) using generalized and linear mixed-effects models, respectively, implemented via the *lme4* package in R (Bates et al., 2015). Mixed-effects

models were chosen because participants responded to multiple stimuli across conditions, creating a repeated-measures structure. Including random intercepts for both participants and items allowed us to account for this non-independence and to generalize findings across individuals and stimuli. Where possible, random slopes for within-participant predictors were included to capture individual differences (Barr et al., 2013). When convergence issues arose due to overfitting, we systematically simplified the random-effects structure, first de-correlating intercepts and slopes and then removing interaction slopes, using likelihood ratio tests to confirm that simplifications did not significantly reduce model fit.

For accuracy, we used a generalized linear mixed-effects model (GLMM) with a binomial logit link function. For RTs, we applied a log transformation to correct for skewness (Baayen & Milin, 2010) and analyzed the data using a linear mixed-effects model (LMM). Continuous predictors (e.g., arousal, word frequency) were standardized (z-scored), and categorical predictors were sum-coded (1, –1) to facilitate interpretation of model coefficients.

Accuracy Results

The final model used to analyze accuracy was specified as: *Accuracy ~ valence × shape × arousal + (1 + shape | ppt) + (1 | item)*

To assess whether *Word2Vec* similarity scores predicted participants' accuracy, we ran a separate GLMM with the following formula: *Accuracy ~ word2vec + (1 | ppt) + (1 | item)*

As shown in Table 1, the GLMM analysis of accuracy revealed that the model had a marginal R^2 of 2.2% and a conditional R^2 of 34.2%, indicating that the fixed effects explained only a small portion of the variance, while random effects related to participants and items accounted for a substantial proportion, as also reflected in the intraclass correlation coefficient (ICC = 33%). No significant effects were found for valence, frame shape, arousal, or their interactions.

Furthermore, *Word2Vec* similarity scores did not significantly predict accuracy when included as a predictor in a separate GLMM model (β = 1.010, *SE* = 1.760, z = 0.574, p = 0.566). This suggests that semantic associations between the words and shape labels also did not impact participants' accuracy.

Table 1

GLMER Model Output for Accuracy in Study 1A

Predictors		β	*SE*	z	p
Intercept		3.984	0.227	17.541	**<0.001**
Valence (Negative)		-0.326	0.181	-1.804	0.071
Shape (Round)		0.118	0.117	1.014	0.311
Arousal		0.199	0.215	0.926	0.354
Valence × Shape		0.009	0.094	0.093	0.926
Valence × Arousal		-0.042	0.215	-0.197	0.844
Shape × Arousal		-0.094	0.106	-0.885	0.376
Valence × Shape × Arousal		-0.084	0.108	-0.776	0.438
Random Effects					
σ^2	3.29				
$\tau_{00\ ppt}$	0.69				
$\tau_{00\ item}$	0.90				
$\tau_{11\ ppt.shape\ (round)}$	0.01				
$\rho_{01\ ppt}$	0.07				
ICC	0.33				
N_{ppt}	81				
N_{item}	64				
Observations	5184				
Marginal R^2 / Conditional R^2	0.022 / 0.342				

RT results

Although words were matched across conditions for word frequency (log occurrences per million) and word length (number of letters), we formally tested the influence of these factors by adding them as predictors in the RT analysis. Word frequency, a well-established predictor of lexical decision performance (Monsell et al., 1989), significantly improved model fit and was retained. In contrast, word length did not contribute significantly and was excluded. This

approach ensured the final model balanced complexity and interpretability while controlling for key psycholinguistic variables.

As in the accuracy analysis, continuous predictors (arousal and word frequency) were standardized (z-scored) to facilitate interpretation. The final model used to analyze RTs was:

log.RT ~ valence × shape × arousal × frequency + 1 (participants) + 1 (items)

Additionally, as with the accuracy analyses, we ran a separate LMM to assess whether *Word2Vec* similarity predicted participants' reaction times (RTs). The model formula was:

log.RT ~ word2vec + (1 | ppt) + (1 | item)

Before analysis, we excluded all filler items and removed incorrect responses for the experimental stimuli. Reaction times (RTs) were further cleaned by discarding trials with extremely fast responses (<250 ms) and those exceeding 2.5 standard deviations above the mean within each condition. This trimming procedure resulted in the exclusion of 3.05% of the observations.

The main results from the linear mixed-effects analysis of RTs are presented in Table 2. The model had a marginal R^2 of 2.0% and a conditional R^2 of 44.5%, indicating that the fixed effects explained a small proportion of the variance in reaction times, while random effects, particularly those related to participants, accounted for a substantial amount, as reflected in the intraclass correlation coefficient (ICC) of 43%. There were no significant main effects of valence, shape, or arousal on RTs (ps > .13). However, word frequency was significant, with higher-frequency words being processed faster (β = -0.022, p = .050), aligning with the well-documented word frequency effect in lexical processing (Monsell et al., 1989).

Among the interaction effects, a significant interaction[4] emerged between valence and shape (β = 0.013, p = .001). To further investigate this effect, we conducted a post hoc analysis,

decomposing the interaction within each valence condition. As shown in Figure 3 (Plot A), and in line with our hypothesis, for negative words, response times were significantly slower when presented in round frames compared to sharp frames (β = 0.028, *SE* = 0.010, *t* = 2.772, *p* = .006, *d* = 0.170). Conversely, for positive words, responses were faster for words in round frames than sharp frames (β = -0.024, *SE* = 0.007, *t* = -3.388, *p* = .001, *d* = - 0.148).

Another significant interaction emerged between shape and arousal (β = -0.008, *p* = .042). Post hoc analyses examined the impact of arousal separately for words in round and sharp frames. For round frames, the effect of arousal on RTs was not significant (β = -0.023, *SE* = 0.013, *t* = -1.745, *p* = .086). Similarly, for sharp frames, no significant effect of arousal was found (β = -0.007, *SE* = 0.013, *t* = -0.527, *p* = .600). Thus, the interaction likely reflects differences in slopes across conditions rather than strong effects within individual conditions. Caution is warranted, as a near-significant three-way interaction between valence, shape, and arousal (β = -0.008, *p* = .051) suggests a more complex pattern, which we address next.

Table 2

LMER Model Output for RTs (log-transformed) in Study 1A

Predictors	*β*	*SE*	*t*	*p*
(Intercept)	6.353	0.018	357.844	**< 0.001**
Valence (Negative)	0.015	0.010	1.506	0.138
Shape (Round)	0.001	0.003	0.298	0.765
Arousal	-0.015	0.012	-1.197	0.236
Frequency	-0.022	0.011	-2.000	**0.050**
Valence × Shape	0.013	0.003	4.253	**<0.001**
Valence × Arousal	-0.005	0.012	-0.422	0.675
Shape × Arousal	-0.008	0.004	-2.034	**0.042**
Valence × Frequency	-0.006	0.011	-0.537	0.594
Shape × Frequency	0.003	0.003	0.909	0.363
Arousal × Frequency	-0.004	0.019	-0.189	0.851
Valence × Shape × Arousal	-0.008	0.004	-1.952	*0.051*
Valence × Shape × Frequency	0.000	0.003	0.022	0.982
Valence × Arousal × Frequency	-0.008	0.019	-0.438	0.663
Shape × Arousal × Frequency	-0.009	0.006	-1.531	0.126

Valence × Shape × Arousal × Frequency	-0.008	0.006	-1.472	0.141

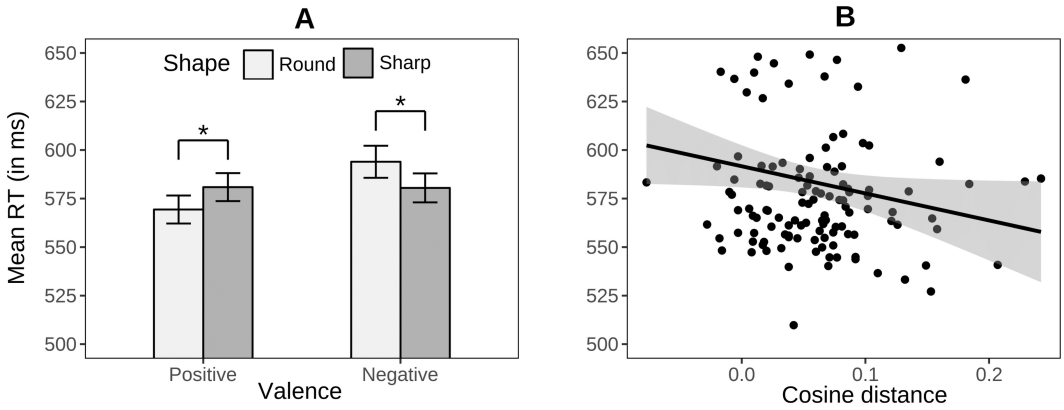
Random Effects	
σ^2	0.03
$\tau_{00\ ppt}$	0.02
$\tau_{00\ item}$	0.00
ICC	0.43
$N_{\ ppt}$	81
$N_{\ item}$	64
Observations	4827
Marginal R^2 / Conditional R^2	0.020 / 0.445

Note. Values in **bold** indicate significant effects ($p < .05$), while values in *italics* indicate effects approaching significance ($p \approx .051$).

To decompose the three-way interaction, we conducted simple slopes analyses, examining how the effect of shape on RTs varied across different levels of arousal, separately for positive and negative words (Figure 4). For positive words, responses were consistently slower when embedded in sharp frames compared to round frames, regardless of arousal level. At moderate arousal (-1 SD), sharp frames led to slower responses than round frames ($\beta = 0.024$, $SE = 0.008$, $t = 3.150$, $p = .002$), and this pattern persisted at high arousal (+1 SD) ($\beta = 0.025$, $SE = 0.011$, $t = 2.294$, $p = .022$). In contrast, for negative words, the effect was different. At moderate arousal (-1 SD), responses were significantly faster for sharp frames than round frames ($\beta = -0.059$, $SE = 0.023$, $t = -2.595$, $p = .009$). However, at high arousal (+1 SD), no significant difference emerged between frame types ($\beta = 0.003$, $SE = 0.010$, $t = 0.347$, $p = .728$). Thus, for negative words, sharp frames facilitated faster processing only under moderate arousal conditions, with this advantage disappearing under heightened arousal.

Figure 3

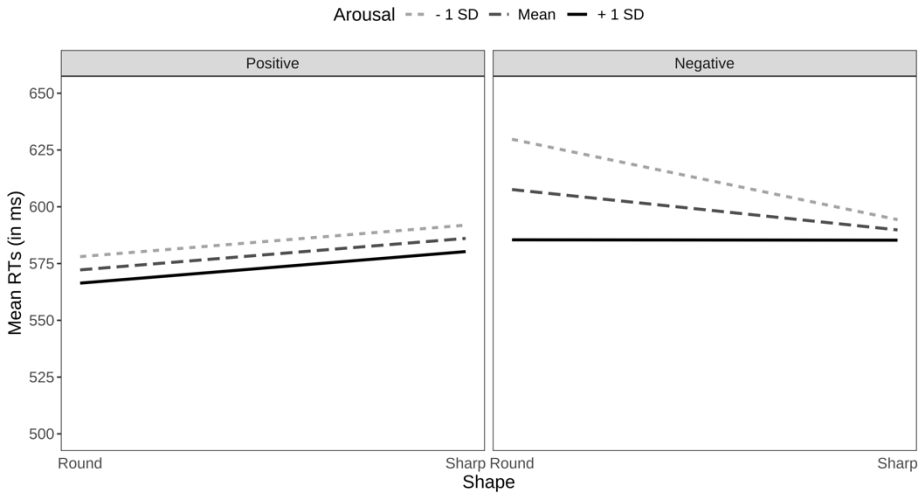
Participants' RTs in Study 1A as a Function of the Interaction Between Valence and Shape (A) and an Effect of Semantic Similarity (B)



Note. Plot A depicts participants' RTs (with 95% CIs) as a function of the interaction between valence and shape. Plot B depicts participants' RTs as a function of word2vec cosines scores, which reflect the similarity between a target word (positive, negative) and a target shape (sharp, round). In Study 1, we found that 'positive-round' word pairs had higher cosines than 'positive-sharp' word pairs; and 'negative-sharp' word pairs had higher cosines than 'negative-round' word pairs. Thus, word2vec cosines scores predict participants' RTs in a similar manner as the interaction between word valence and visual shape.

Figure 4

Participants' RTs in Study 1A as a Function of the Interaction Between Valence, Shape, and Arousal



Note. Solid line (+1SD) refers to high arousal, and dashed line (-1SD) refers to moderate arousal.

Finally, we tested whether *Word2Vec* similarity scores predicted response times (RTs) in a separate model. As shown in Figure 3 (Panel B), *Word2Vec* scores significantly influenced RTs, with higher semantic similarity between target words and their associated shape labels predicting faster RTs (β = -0.204, SE = 0.059, t = -3.48, $p < .001$). This finding suggests that words more strongly associated with a particular shape category (e.g., "sharp" or "round") in linguistic contexts were more readily mapped onto these conceptual distinctions, reinforcing the role of language in shaping conceptual knowledge.

At a broader theoretical level, these results demonstrate that shape-emotion associations can be extracted computationally from language, indicating that linguistic structure encodes not only perceptual but also affective information. These findings are consistent with the Symbol Interdependency Hypothesis (Louwerse, 2011), which posits that language reflects and reinforces embodied experiences by capturing statistical regularities in the environment.

Discussion

Study 1A showed that shape–emotion congruency facilitates word recognition, with faster responses to positive words in round frames and to negative words in sharp frames. *Word2Vec* similarity scores also predicted participants' reaction times, suggesting that linguistic co-occurrence patterns partly contribute to these associations. However, arousal effects were less robust, as the observed effects appeared primarily driven by valence under moderate arousal conditions. Overall, these findings provide initial evidence that both visual shape and linguistic distributional information contribute to the processing of emotion–shape associations.

Study 1B

Study 1B examined whether people explicitly associate positively- and negatively-valenced words with rounded or sharp shapes. Participants completed a rating task administered through

Qualtrics, where they were presented with positive and negative words one at a time and asked to rate the extent to which each word was associated with something visually round/curved versus sharp/angular.

Participants

Eighty-two native Portuguese university students[5] (M_{age} = 20.85, SD_{age} = 2.63; 66 females) participated in Study 1B. Participants took part in exchange for course credit and provided informed consent prior to participation.

Procedure

The study was conducted in Qualtrics. Participants saw positively- and negatively-valenced words and were asked to indicate the degree to which they associate each word with something visually round/curved or sharp/angular on a 7-point scale (1 = Strongly associated with something round/curved; 7 = Strongly associated with something sharp/angular). The presentation order of the words was randomized, and each participant rated one word at a time.

Results

Analysis plan

Participants' ratings were analyzed with the cumulative link mixed model implemented via "ordinal" R package (Christensen, 2018). The full model included valence (positive vs. negative) and arousal (continuous variable; from the database by Soares et al., 2012) and their interaction as fixed effects; by-participant and by-word random intercepts; and a slope for valence.

In addition, *Word2vec* scores (i.e., similarities between shapes and positively-/negatively-valenced words) were analyzed using a standard linear regression (i.e., not a mixed-effects model) in R. Here, the fixed effects included valence, arousal, shape type (round vs. sharp), and their interactions. Follow-up analyses were conducted if a significant interaction was observed.

Of primary interest was whether participants' ratings and word embeddings would differ in predicting the association between word valence and shape.

Participants' ratings

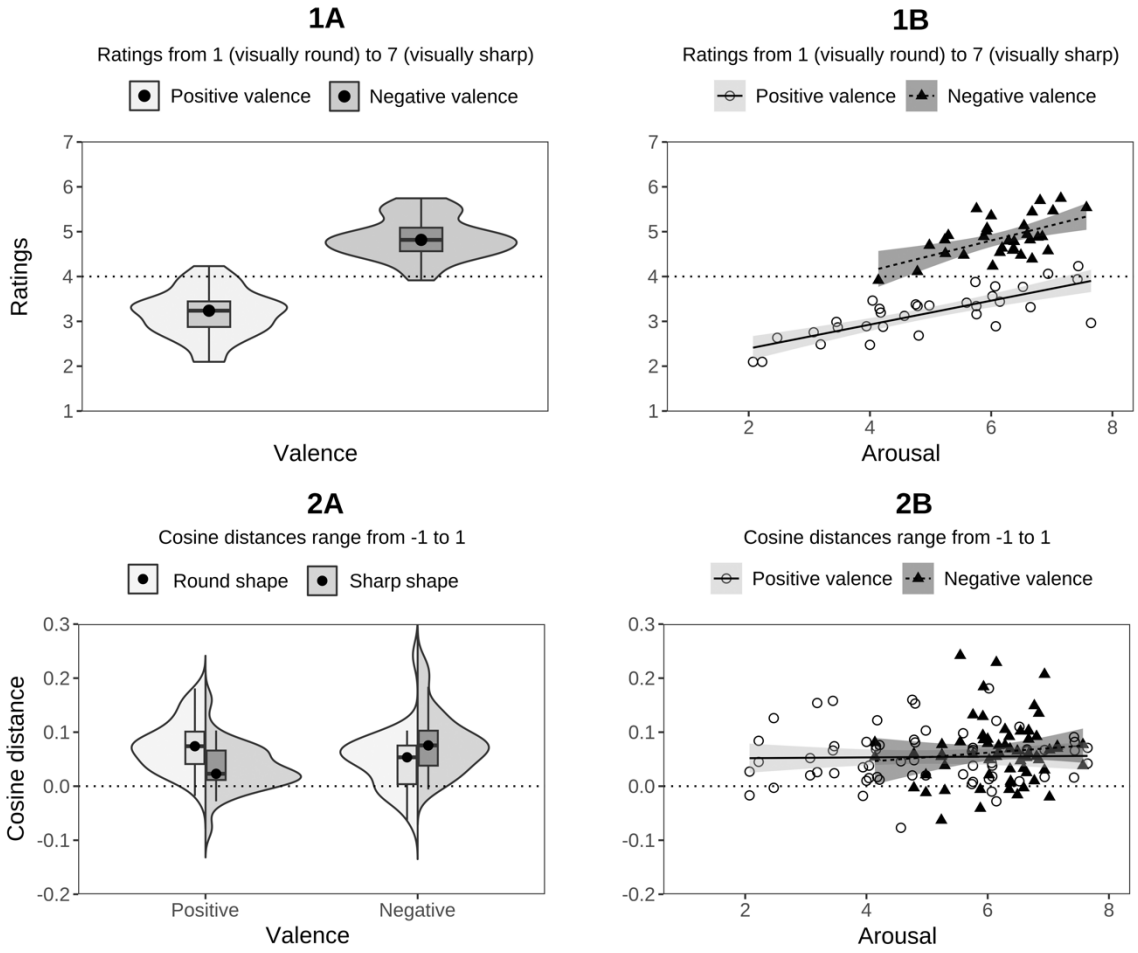
Major results are presented in Figure 5 (1A and 1B). The model had a marginal R^2 of 26.1% and a conditional R^2 of 50.1%, indicating that the fixed effects explained a substantial portion of the variance in ratings, with additional variance accounted for by the random effects of participants and items. There was a significant main effect of valence ($\beta = 0.948$, $SE = 0.138$, $z = 6.877$, $p < .001$) with higher ("sharp") responses for negatively-valenced words ($M = 4.86$, $SD = 1.53$) compared to positively-valenced words ($M = 3.18$, $SD = 1.58$). In addition, there was a main effect of arousal ($\beta = 0.601$, $SE = 0.094$, $z = 6.395$, $p < .001$), suggesting that higher levels of emotional arousal led to higher ("sharp") ratings. Finally, there was no evidence of the interaction between the two factors ($\beta = 0.106$, $SE = 0.094$, $z = 1.130$, $p = .258$).

Word2Vec scores

Major results are presented in Figure 5 (2A and 2B). The only significant result was an interaction between valence and shape ($\beta = -0.181$, $SE = 0.005$, $z = -3.320$, $p = .001$). As with participants' ratings, follow-up analyses revealed that negatively-valenced words were more strongly associated with sharp/angular than round/curved objects ($\beta = -0.035$, $SE = 0.017$, $z = -2.065$, $p = .041$). The reverse was true for positively-valenced words ($\beta = 0.038$, $SE = 0.014$, $z = 2.709$, $p = .016$). No other effects were significant ($t < 1$).

Figure 5

Association Between Emotion and Shape Using Participants' Ratings and Word2vec Scores in Study 1B



Note. The points and error bars in plots 1A and 2A show fitted values (medians with 95% CIs); and violins (1A) and split violins (2A) show the distribution of mean observed values per word. Plots 1B and 2B are scatterplots with lines of best fit and 95% CIs. The dashed line in plots 1A and 2A indicates the scale's mid-point. The dashed line in plots 1B and 2B indicate orthogonal vectors (i.e., 0 indicates that the words used in the analyses are unrelated). Negative cosine values between -1 and 0 similarly suggest that the words are unrelated. The closer the cosine value to 1, the greater the match between the words.

Discussion

The results confirmed our prediction that language comprehenders associate positive words with round/curved objects and negative words with sharp/angular objects. Importantly, this association was also reflected in linguistic patterns, as it was successfully predicted by the word

embedding analysis. The major difference between participants' ratings and *Word2Vec* scores concerns emotional arousal. As expected, participants were affected by the intensity of an emotion compared to a semantic space model that did not capture the contribution of this dimension (Figure 5, 2B).

Overall, these results align with those from Study 1A, where similar valence-shape congruency effects were observed in reaction times during an implicit lexical decision task. Both studies demonstrate that the association between emotional valence and visual shape not only influences explicit judgments but also impacts online language processing. However, arousal strongly influenced participants' responses but was not captured by the semantic model, suggesting it reflects a flexible, context-driven aspect of meaning beyond static language associations.

Study 2

While Studies 1A and 1B have advanced our understanding of the relationship between shape and emotion, the role of arousal remained unclear. Specifically, in Study 1A, responses to positive words showed consistent shape–valence effects regardless of arousal, but results for negative words suggested that high arousal might disrupt shape–emotion associations. Importantly, however, as most stimuli in Studies 1A and 1B were of moderate arousal, we could not determine whether arousal independently influences these associations or simply amplifies valence effects.

To address this issue and, consequently, ensure a sharper contrast between conditions, in Study 2, we systematically manipulated both valence and arousal by selecting and categorizing words into four distinct groups: High Valence-High Arousal (HVHA), High Valence-Low

Arousal (HVLA), Low Valence-High Arousal (LVHA), and Low Valence-Low Arousal (LVLA).

Furthermore, as before, we focused on abstract words (mean concreteness rating = 2.50) and controlled for word length and frequency. To further minimize confounds, we also added lexical neighborhood constraints, selecting only words with a maximum of one lexical neighbor. We also refined the experimental instructions, removing any reference to visual frames to further reduce potential bias, following Sučević et al. (2013).

In sum, Study 2 tested two main questions: (1) Do valence-shape associations persist when arousal is strictly controlled? (2) Does arousal systematically modulate or override these associations? Finally, we tested whether *Word2Vec* continues to predict RTs when arousal is experimentally manipulated, clarifying the relative contributions of linguistic and perceptual factors to emotion-shape mappings.

Method

Participants

Eighty native Portuguese students participated in Study 2 (*M*age = 23.74, *SD*age = 9.93; 63 females) in exchange for course credit and provided informed consent before participation.

Design and Materials

Study 2 employed a 2 (valence: positive vs. negative) × 2 (shape: sharp vs. round) × 2 (arousal: low vs. high) within-participants design. The study comprised 112 stimuli (56 words and 56 nonwords). Unlike Studies 1A and 1B, where arousal levels were mostly moderate, Study 2 explicitly contrasted high- and low-arousal words to more systematically test arousal's role in shape-emotion associations.

The materials were largely the same as in Studies 1A and 1B, with a few key modifications. First, target words were newly selected to meet stricter arousal criteria, creating four groups: High Valence-High Arousal (HVHA; e.g., "adventure"), High Valence-Low Arousal (HVLA; e.g., "wisdom"), Low Valence-High Arousal (LVHA; e.g., "danger"), and Low Valence-Low Arousal (LVLA; e.g., "lonely"). Second, to minimize lexical similarity effects, only words with at most one lexical neighbor were included, with most having zero neighbors. Full specifications of the word stimuli are provided in Appendix B.

Procedure

The procedure closely followed that of Study 1A, with one refinement: the experimental instructions were modified to align with Sučević et al. (2013) by removing explicit references to the visual frames. This change aimed to minimize participants' focus on the shapes.

Results

Accuracy Results

The analysis plan and model simplification procedures were the same as in Study 1A. The final model used to report results was:

Accuracy ~ valence × shape × arousal + (1 | ppt) + (1 | item)

Table 3

GLMER Model Output for Accuracy in Study 2A

Predictors	*β*	*SE*	*z*	*p*
Intercept	4.240	0.216	19.639	**<0.001**
Valence (High)	0.074	0.161	0.457	0.648
Shape (Angular)	-0.112	0.098	-1.144	0.253
Arousal (High)	0.137	0.161	0.855	0.393
Valence × Shape	-0.039	0.099	-0.394	0.694
Valence × Arousal	0.118	0.161	0.733	0.463
Shape × Arousal	0.082	0.098	0.836	0.403
Valence × Shape × Arousal	-0.028	0.098	-0.284	0.777

Random Effects	
σ^2	3.29
$\tau_{00\ ppt}$	0.53
$\tau_{00\ item}$	0.76
ICC	0.28
$N_{\ ppt}$	80
$N_{\ item}$	56
Observations	4480
Marginal R^2 / Conditional R^2	0.013 / 0.291

The main results of the accuracy analysis for Study 2A are shown in Table 3. The model presents a marginal R^2 of 1.3% and a conditional R^2 of 29.1%, indicating that the fixed effects explained only a small proportion of the variance, while random effects related to participants and items accounted for a substantial share, as also reflected in the intraclass correlation coefficient (ICC = 28%).

As in Study 1A, GLMM analyses revealed no significant main effects of valence, shape, or arousal on accuracy, nor any significant interactions among these variables (*ps* > .25). Similarly, the results of a separate model with *Word2Vec* similarity scores as a predictor showed no significant effect on accuracy (β = -0.089, *SE* = 1.316, *z* = -0.067, *p* = .946), consistent with Study 1A, where semantic similarity also had no measurable impact on performance..

Analysis Plan for Response Times (RTs)

We approached the analysis of RTs in the same way as in Study 1A. The trimming procedures led to the loss of 2.64% of observations. The final model to analyze RTs was:

log.RT ~ valence × shape × arousal × frequency + (1 | ppt) + (1 | item).

RT Results

The main results of the RT analysis for Study 2A are presented in Table 4. The model had a marginal R^2 of 1.1% and a conditional R^2 of 34.2%, indicating that the fixed effects explained only a small portion of the variance in RTs, while random effects, primarily at the participant

level, accounted for a substantial share, as reflected in the intraclass correlation coefficient (ICC = 34%).

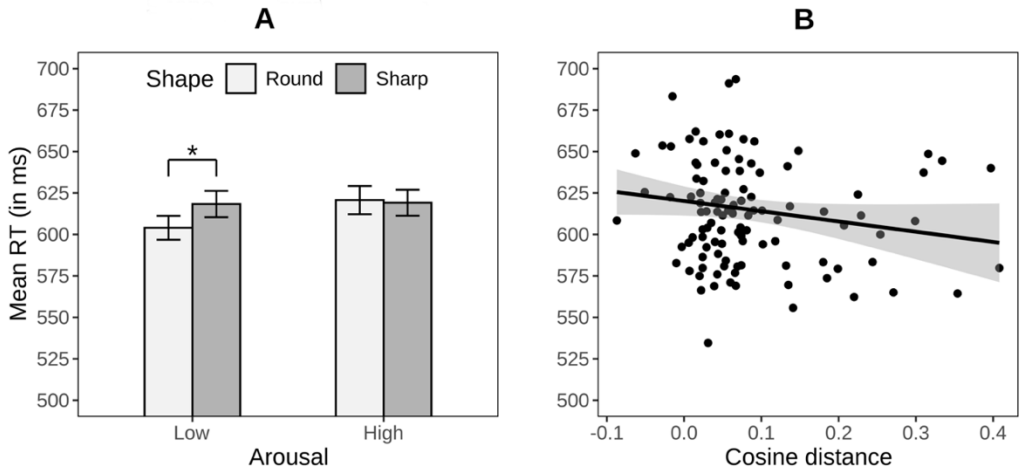
There were no significant main effects of valence, arousal, or picture type on RTs (*ps* > .068). (*ps* > .068). However, word frequency significantly influenced response times, with higher-frequency words being processed faster (β = -0.014, p = .026).

Among the interaction effects, the only significant interaction emerged between shape and arousal (β = -0.005, p = .038). To explore this interaction further, we conducted post hoc analyses decomposing it within each arousal condition. As shown in Figure 6 (Panel A), for high-arousal words, RTs did not significantly differ between angular and rounded shapes (β = -0.001, SE = 0.007, t = -0.181, p = .856, d = 0.008). In contrast, for low-arousal words, RTs were significantly slower when words were embedded in angular shapes compared to rounded shapes (β = 0.020, SE = 0.008, t = 2.695, p = .014, d = 0.124). Thus, shape-emotion congruency effects were observed only for low-arousal words, with rounded shapes facilitating faster responses.

Finally, in a separate model, we examined whether *Word2Vec* similarity scores predicted RTs. As shown in Figure 6 (panel B), the results showed that while the effect of *Word2Vec* scores did not reach statistical significance (β = -0.063, SE = 0.038, t = -1.68, p = .093), higher semantic similarity between positive/negative words and their associated shape labels tended to be linked to faster responses.

Figure 6

Participants' RTs in Study 2 as a Function of the Interaction Between Arousal and Shape (A) and an Effect of Semantic Similarity (B)



Note. Plot A depicts participants' RTs (with 95% CIs) as a function of the interaction between arousal and shape. Plot B depicts participants' RTs as a function of word2vec cosines scores, which reflect the similarity between a target word (positive, negative) and a target shape (sharp, round).

Table 4

LMER Model Output for RTs (log-transformed) in Study 2

Predictors	*β*	*SE*	*t*	*p*
Intercept	6.404	0.014	468.581	**<0.001**
Valence (High)	-0.007	0.006	-1.231	0.225
Arousal (High)	0.007	0.006	1.262	0.213
Shape (Sharp)	0.005	0.003	1.825	0.068
Frequency	-0.014	0.006	-2.305	**0.026**
Valence × Arousal	-0.008	0.006	-1.401	0.168
Valence × Shape	-0.004	0.003	-1.595	0.111
Arousal × Shape	-0.005	0.003	-2.076	**0.038**
Valence × Frequency	-0.004	0.006	-0.594	0.555
Arousal × Frequency	0.003	0.006	0.532	0.597
Shape × Frequency	-0.001	0.003	-0.378	0.705
Valence × Arousal × Shape	0.001	0.003	0.340	0.734
Valence × Arousal × Frequency	-0.001	0.006	-0.102	0.919
Valence × Shape × Frequency	0.001	0.003	0.263	0.792
Arousal × Shape × Frequency	0.001	0.003	0.428	0.669
Valence × Arousal × Shape × Frequency	0.002	0.003	0.600	0.548

Random Effects	
σ^2	0.03
$\tau_{00\ ppt}$	0.01
$\tau_{00\ item}$	0.00
ICC	0.34
$N_{\ ppt}$	80
$N_{\ item}$	56
Observations	4244
Marginal R^2 / Conditional R^2	0.011 / 0.342

Note. Values in **bold** indicate significant effects ($p < .05$)

Discussion

Taken together, the results suggest that arousal, rather than valence, played a dominant role in shaping RTs when it was experimentally manipulated, in contrast to Study 1A, where valence effects were more pronounced. Furthermore, the predictive power of *Word2Vec* similarity scores diminished compared to Study 1A, where valence was the key variable. This suggests that the distributional semantics captured by *Word2Vec* may be more reflective of valence-driven associations than arousal-based ones, reinforcing the idea that linguistic co-occurrence patterns may encode valence more efficiently than arousal.

Additional Analyses: Gamma Regression on Raw RTs

To ensure that the observed effects did not depend on the specific trimming procedures applied in our main analyses, we reanalyzed the RT data from Studies 1A and 2 using a generalized linear mixed-effects model (GLMM) with a Gamma distribution and log link (see Table 5, which reports beta coefficients and p-values from the two models). This approach, recommended for positively skewed data (Lo & Andrews, 2015; see also Ostarek et al., 2019), allows modeling of raw RTs without transformation or arbitrary outlier removal, while preserving the full random-effects structure. We therefore included all RT data, excluding only extremely fast (i.e., implausibly fast) responses (< 250 ms).

Table 5

RT Analyses Using LMM (Log RTs) and GLMM (Gamma) in Studies 1A and 2

Predictor	*Study 1A*		*Study 2*	
	Log RTs (LMM)	*Raw RTs (GLMM)*	*Log RTs (LMM)*	*Raw RTs (GLMM)*
Intercept	**β = 6.353, p < .001**	**β = 6.395, p < .001**	**β = 6.404, p < .001**	**β = 6.441, p < .001**
Valence (V)	β = 0.015, p = .138	β = 0.016, p = .306	β = –0.007, p = .225	β = –0.005, p = .569
Shape (S)	β = 0.001, p = .765	β = 0.004, p = .289	β = 0.007, p = .213	β = 0.009, p = .327
Arousal (A)	β = -0.015, p = .236	β = -0.020, p = .302	β = 0.005, p = .068	β = 0.005, p = .157
Frequency (F)	**β = -0.022, p = .050**	β = -0.029, p = .080	**β = –0.014, p = .026**	β = –0.016, p = .114
V × S	**β = 0.013, p = .001**	**β = 0.011, p = .003**	β = –0.008, p = .168	β = –0.009, p = .315
V × A	β = -0.005, p = .675	β = -0.004, p = .849	β = –0.004, p = .111	β = –0.005, p = .086
S × A	**β = -0.008, p = .042**	β = -0.009, p = .068	**β = –0.005, p = .038**	**β = –0.008, p = .018**
V × F	β = -0.006, p = .594	β = -0.009, p = .601	β = –0.004, p = .555	β = –0.003, p = .772
S × F	β = 0.003, p = .363	β = 0.000, p = .988	β = 0.003, p = .597	β = 0.008, p = .433
A × F	β = -0.004, p = .851	β = 0.000, p = .998	β = –0.001, p = .705	β = 0.003, p = .403
V × S × A	*β = -0.008, p = .051*	β = -0.008, p = .112	β = 0.001, p = .734	β = 0.000, p = .942
V × S × F	β = 0.000, p = .982	β = 0.002, p = .681	β = –0.001, p = .919	β = –0.001, p = .897
V × A × F	β = -0.008, p = .663	β = -0.010, p = .733	β = 0.001, p = .792	β = 0.004, p = .235
S × A × F	β = -0.009, p = .126	β = -0.009, p = .180	β = 0.001, p = .669	β = 0.000, p = .990
V × S × A × F	β = -0.008, p = .141	β = -0.011, p = .112	β = 0.002, p = .548	β = 0.001, p = .848

Note. Values in **bold** indicate statistically significant effects. *Italicized* values indicate marginal effects. Gray shading highlights effects that were significant in both types of models within the same study.

As can be seen from Table 5, in both Study 1A and Study 2, the critical effects observed in the main analyses were confirmed when reanalyzing the raw RT data using Gamma GLMM. Specifically, the valence × shape interaction in Study 1A ($\beta = 0.011$, $SE = 0.004$, $t = 2.949$, $p = .003$) and the shape × arousal interaction in Study 2 ($\beta = –0.008$, $SE = 0.003$, $t = –2.366$, $p = .018$) remained significant across both the log-transformed LMM and the raw RTs Gamma GLMM analyses (see shaded rows in Table 5). Thus, these effects appear robust across analytic approaches. Conversely, the 3-way (valence × shape × arousal) interaction in Study 1A, which was approaching significance in the primary analysis with log RTs ($p = .051$), did not reach significance in the Gamma GLMM ($\beta = –0.008$, $SE = 0.005$, $t = –1.591$, $p = .112$). This suggests

that this interaction should be interpreted as a suggestive trend rather than a reliable effect. Overall, these results increase confidence that the observed valence-shape (Study 1A) and valence-arousal (Study 2) interactions reflect consistent effects that do not depend on the specific assumptions of RT distributional shape or the use of trimming procedures.

General Discussion

This research examined how shape-emotion associations are influenced by valence, arousal, and linguistic co-occurrence patterns. Across three studies, we tested whether positive and negative words are associated with round and sharp shapes, respectively, and whether *Word2Vec* could predict these mappings.

In Study 1A, we used an implicit lexical decision task. Using a set of words that varied primarily in valence (with arousal levels mostly moderate), we found that participants responded significantly faster when the valence of a word was congruent with the shape of the frame in which it appeared (i.e., positive-round, negative-sharp). Notably, participants' RTs were also predicted by *Word2Vec* cosine similarity scores, suggesting that language-based distributional patterns encode these associations.

In Study 1B, we used an explicit rating task that confirmed the findings from Study 1A: participants systematically associated positive words with roundness and negative words with sharpness, and *Word2Vec* predicted shape-emotion ratings. Together, Studies 1A and 1B show that both online and explicit conceptual processing reflect valence-shape associations, which are also mirrored in language.

Finally, in Study 2, we extended these findings by systematically manipulating valence and arousal. The results revealed that arousal, rather than valence, shaped RTs: participants responded faster to low-arousal words presented in round frames, but no consistent shape-

emotion associations emerged for high-arousal words. Moreover, *Word2Vec*'s predictive power weakened, suggesting that linguistic distributional patterns capture valence-based associations more reliably than arousal-based ones.

One of the most interesting patterns in our findings is the shift from a valence-shape effect in Studies 1A /1B to an arousal-shape effect in Study 2. One explanation for this shift is that low-arousal words (e.g., "peace" or "sadness") do not differ fundamentally in their function based on valence. More specifically, both positive and negative low-arousal words typically describe passive, low-energy, and slow-moving states, which align with the smooth, continuous contours of round shapes (e.g., Blazhenkova & Kumar, 2017). In contrast, high-arousal words (e.g., "danger" or "excitement"), while both energetic, activate distinct motivational systems.

According to Lang and Bradley (2013), high-arousal negative emotions (e.g., "danger") primarily engage the defensive motivational system, supporting threat perception, defensive reactions, and avoidance behaviors (e.g., Larson et al., 2017). Conversely, high-arousal positive emotions (e.g., "excitement") engage the appetitive motivational system, promoting approach behaviors, encouraging exploration and engagement (e.g., Cudo et al., 2018). As these two categories of high-arousal words have opposing behavioral functions (i.e., avoidance versus approach), their association with shape may be less robust than that of low-arousal words, thus reducing the likelihood of a systematic link between high arousal and sharpness. Thus, this explanation is consistent with Lang and Bradley's (2013) proposal that both appetitive and defensive cues may elicit similar arousal levels but activate different coping mechanisms depending on the organism's current goal.

Another possibility, outlined at the start of this article, is that high arousal narrows attention (Steblay, 1992; Yerkes & Dodson, 1908), making participants focus more on the emotional

intensity of the stimuli and less on secondary features such as shape congruency. In contrast, low-arousal words, which demand less emotional processing, may allow participants to maintain broader attentional scope and integrate shape-emotion associations more consistently. A related but distinct explanation comes from Mather and Sutherland's (2011) arousal-biased competition (ABC) theory, which suggests that arousal does not simply reduce attentional breadth but intensifies competition between mental representations. Under high arousal, cognitive resources are preferentially allocated to motivationally salient features, while lower-priority cues are suppressed. In the present task, the emotional meaning of high-arousal words likely acted as a high-priority input, dominating attentional processing. In contrast, shape information, being motivationally neutral, received less processing under high-arousal conditions. Together, these accounts converge in suggesting that high arousal impairs shape–emotion associations by biasing processing toward emotional content.

However, if attentional narrowing might explain the influence of arousal, one might wonder why valence-shape associations were not reliably observed even under low-arousal conditions in Study 2. To understand this, it is important to consider a key methodological difference between the studies. In Studies 1A and 1B, stimuli were primarily selected based on valence, with arousal statistically controlled but not systematically manipulated. As a result, arousal and valence often varied together. As shown in Appendix A, negative words in those studies tended to be higher in arousal than positive ones. Interestingly, this mirrors findings from Kuppens et al. (2013), who showed that arousal naturally increases at both extremes of the valence scale, particularly for negative emotions. Thus, the stimuli in Study 1 likely reflected a naturally occurring alignment between valence and arousal, which may have facilitated stronger shape-emotion associations.

In contrast, Study 2 used a fully crossed design that deliberately separated these two emotional dimensions, minimizing their covariation. This clearer separation may have disrupted the alignment that had previously supported valence-shape mappings. Consequently, the absence of valence-shape effects in the low-arousal condition of Study 2 likely reflects these methodological differences rather than some contradiction of the patterns observed in Study 1. Indeed, even in Studies 1A and 1B, arousal effects were detected alongside valence effects (specifically, in the analysis of log RTs), suggesting that arousal already tended to influence participants' responses. Study 2 simply amplified these effects by systematically manipulating arousal, allowing it to emerge as the dominant factor when compared to valence.

At a broader level, our findings suggest that valence provides a stable basis for shape-emotion associations when arousal is moderate but can be overridden when arousal is salient. This echoes research showing that negative emotions like anger (high-arousal) and sadness (low-arousal) differ in their shape associations (Sievers et al., 2019).

Beyond perceptual factors, our results contribute to debates on how language reflects embodied experiences. While distributional models like *Word2Vec* capture valence-shape mappings, they fail to fully encode more context-sensitive, arousal-based associations. This aligns with findings by Varma et al. (2023) and Recchia and Jones (2015), suggesting that linguistic patterns mirror stable emotional dimensions but tend to struggle with dynamic experiential ones. Our findings thus underscore the complementary roles of culturally stabilized linguistic patterns and embodied, context-specific mechanisms in shaping how abstract emotional concepts are mentally represented and processed. An important novelty of the present research is its focus on abstract concepts rather than concrete ones, offering new insights into how emotional and perceptual mappings operate for less perceptually grounded concepts. Prior

studies have primarily explored concrete words, which tend to have more direct ties to sensory experience (e.g., Sučević et al., 2013), whereas our findings highlight that even abstract concepts show shape-emotion associations.

Nonetheless, further research is needed to deepen this understanding. Even within abstract concepts, linguistic features such as word class (e.g., noun, verb, adjective) may modulate these associations and deserve closer investigation. Moreover, extending computational modeling beyond *Word2Vec* to more advanced transformer-based models (e.g., BERT, GPT) could offer a more detailed picture of how valence and arousal are represented in language.

There is also a broader limitation that warrants attention. Our participants were native Portuguese speakers, which limits the cross-cultural generalizability of the findings (e.g., Kitayama et al., 2000). Future research should investigate how cultural and linguistic differences might moderate emotion-shape associations, including whether the frequency and salience of specific emotional experiences within a culture influence how abstract concepts are emotionally and perceptually grounded.

In conclusion, this research demonstrates that both valence and arousal shape emotion-related associations with visual forms, but their influence depends on the salience of arousal. Valence-based mappings (positive–round, negative–sharp) remain stable when arousal is moderate, yet arousal can override these associations when explicitly manipulated (high vs. low). Moreover, our findings suggest that valence is more systematically encoded in linguistic representations than arousal. These results highlight the importance of considering both linguistic and perceptual mechanisms when investigating the links between shape and emotional meaning.

Data Availability Statement

The materials, data, and scripts have been made available at https://osf.io/szamu/?view_only=dfeecb7362b04ac68c133599dd48b240.

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Footnotes

1. More specifically, we used a linear (rather than generalized linear) mixed-effects model to analyze RTs from Yao et al.'s (2022) study, maintaining consistency with our approach. Following Kumle et al. (2021), we: (a) ran a linear mixed model on Yao et al.'s Experiment 2 data, (b) computed 90% power estimates for sample sizes of 60–120, setting a t-value of 2 as the threshold for significance, and (c) conducted 1000 simulations using "mixedpower" defaults.

2. "Sharp" and "round" were selected based on their high frequency in SubtlexUS (Brysbaert & New, 2009): "round" = 3393 occurrences; "sharp" = 1213. Alternatives like "rounded" (83), "curved" (31), and "angular" (7) were much less frequent.

3. Word embedding analysis assumes that words appearing in similar contexts are semantically related, measured by cosine similarity (ranging from -1 to 1), with higher values indicating greater similarity.

4. For this and other analyses reported in this paper, we approached the decomposition of the significant interaction in the following way. For interactions involving only categorical predictors, we performed follow-up analyses using the "emmeans" R package (Lenth, 2017) while controlling for family wise error rate using the holm method (Aickin & Gensler, 1996). For interactions with continuous predictors, we performed a simple slopes analysis with the "interactions" R package (Long, 2019). This package accepts a regression model (with an interaction term) as input and automates the simple slopes procedure.

5. Participants were the same as in Study 1A.

Appendix A

List of Word Stimuli in Portuguese with English Translation in Parentheses (Studies 1A and 1B)

#	Positive Stimuli					Negative Stimuli				
	Word	*Valence*	*Arousal*	*Frequency*	*Length*	*Word*	*Valence*	*Arousal*	*Frequency*	*Length*
1	aconchego (cuddle)	7.49	2.07	0.54	9	acusação (lawsuit)	2.80	6.64	22.57	8
2	acordo (agreement)	6.15	4.18	201.63	6	avareza (greed)	3.12	4.98	0.97	7
3	alegria (joy)	8.38	5.76	28.15	7	crise (crisis)	2.50	5.93	27.76	5
4	amabilidade (kindness)	7.46	4.00	2.37	11	culpa (fault)	2.28	6.49	197.01	5
5	ambição (ambition)	6.28	6.07	6.86	7	depressão (depression)	1.88	6.36	11.13	9
6	ânimo (cheer)	7.14	5.59	3.93	5	desavença (quarrel)	2.66	5.92	0.65	9
7	anjo (angel)	6.83	3.19	32.79	4	desgosto (grief)	2.28	5.24	4.28	8
8	aventura (adventure)	7.48	7.42	22.19	8	dívida (debt)	2.91	6.38	19.38	6
9	comédia (comedy)	7.86	5.76	8.95	7	dor (ache)	1.89	6.84	109.24	3
10	confiança (trust)	7.78	3.94	53.74	9	escumalha (scum)	3.10	5.88	4.78	9
11	conforto (comfort)	7.74	2.22	10.16	8	falhado (loser)	2.61	5.55	15.19	7
12	cortesia (politeness)	6.50	4.16	8.66	8	fracasso (failure)	1.78	6.37	10.95	8
13	diversão (fun)	8.23	6.65	31.47	8	fraude (fraud)	2.38	6.59	18.55	6
14	encanto (charm)	7.40	4.80	8.51	7	guerra (war)	2.30	5.76	258.97	6
15	esperança (hope)	7.42	3.45	72.14	9	incómodo (discomfort)	3.45	6.14	7.79	8
16	espírito (spirit)	5.86	4.04	63.33	8	inferno (hell)	3.04	6.00	92.39	7
17	excitação (thrill)	7.14	7.44	5.78	9	malévolo (evil)	2.48	5.24	0.54	8
18	êxtase (ecstasy)	7.32	6.94	3.69	6	massacre (massacre)	1.56	7.57	8.81	8
19	festa (party)	7.57	6.52	210.34	5	miséria (misery)	1.79	6.18	7.46	7
20	gozo (enjoyment)	5.45	5.74	6.33	4	motim (riot)	4.12	6.29	5.93	5
21	humor (humor)	7.61	4.76	36.18	5	multa (penalty)	2.29	6.68	11.30	5
22	lotaria (lottery)	6.83	6.02	5.28	7	pecado (sin)	4.85	5.29	22.51	6
23	mobilidade (mobility)	6.52	4.98	1.40	10	perigo (danger)	3.23	7.15	81.89	6
24	paixão (passion)	8.18	7.65	24.92	6	pobreza (poverty)	1.96	6.02	8.20	7
25	paraíso (paradise)	7.89	4.22	25.22	7	pressão (pressure)	3.10	6.94	63.89	7
26	paz (peace)	7.82	2.47	196.39	3	raiva (rabies)	2.64	6.81	38.89	5
27	progresso (progress)	7.24	4.79	17.53	9	revolta (revolt)	3.82	6.54	6.61	7
28	promoção (promotion)	7.12	6.14	12.21	8	sofrimento (pain)	1.92	6.77	24.83	10
29	reunião (reunion)	5.35	4.57	86.14	7	solidão (loneliness)	2.10	4.78	8.77	7
30	santo (saint)	5.19	3.07	56.78	5	suicídio (suicide)	1.82	7.02	30.35	8
31	saúde (health)	7.38	3.47	71.76	5	tédio (ennui)	2.43	4.14	3.70	5
32	sorte (bliss)	7.48	6.08	292.44	5	tortura (torture)	1.82	6.68	15.73	7
	TOTAL	**7.13**	**4.94**	**50.24**	**6.94**		**2.59**	**6.16**	**35.66**	**6.84**

Note. Ratings for valence and arousal are based on a 9-point scale (Soares et al., 2012). Length is expressed in the number of letters.

Appendix B

List of Word Stimuli in Portuguese with English Translation in Parentheses (Study 2)

#	Positive Stimuli						Negative Stimuli					
	Word	*Condition*	*Valence*	*Arousal*	*Frequency*	*Length*	*Word*	*Condition*	*Valence*	*Arousal*	*Frequency*	*Length*
1	ambição (ambition)	HVHA	6.28	6.07	33.62	7	acusação (lawsuit)	LVHA	2.8	6.64	68.84	8
2	âmimo (cheer)	HVHA	7.14	5.59	19.25	5	afectar (impair)	LVHA	3.61	5.62	107.96	7
3	atrevido (bold)	HVHA	6.32	5.78	3.39	8	anseio (desire)	LVHA	4.38	6.47	7.53	6
4	aventura (adventure)	HVHA	7.48	7.42	32.57	8	ciúme (jealousy)	LVHA	3.04	6.34	12.95	5
5	curioso (curioso)	HVHA	6.39	5.23	44.42	7	diabo (devil)	LVHA	3.81	5.04	33.19	5
6	desejo (wish)	HVHA	7.35	6.86	100.61	6	dívida (debt)	LVHA	2.91	6.38	67.8	6
7	êxtase (ecstasy)	HVHA	7.32	6.94	6.05	6	estúpido (stupid)	LVHA	3.69	5.63	18.07	8
8	famoso (famous)	HVHA	6.31	5.21	57	6	execução (execution)	LVHA	4.25	5.63	66.99	8
9	festive (festive)	HVHA	7.76	7.19	8.45	7	horror (horror)	LVHA	2.88	6.64	21.71	6
10	glória (glory)	HVHA	7.05	5.28	20.42	6	incómodo (discomfort)	LVHA	3.45	6.14	19.62	8
11	promoção (promotion)	HVHA	7.12	6.14	50.28	8	obsessão (obsession)	LVHA	2.89	6.24	8.7	8
12	rápido (quick)	HVHA	5.98	6.24	113.32	6	perigo (danger)	LVHA	3.23	7.15	80.69	6
13	veloz (swift)	HVHA	6.36	5.78	6.85	5	pressão (pressure)	LVHA	3.1	6.94	135.53	7
14	vencedor (champion)	HVHA	7.79	6.58	62.06	8	receoso (afraid)	LVHA	3.2	6.08	5.68	7
		TOTAL	**6.90**	**6.17**	**39.88**	**6.64**		**TOTAL**	**3.37**	**6.21**	**46.80**	**6.79**
15	adorável (adorable)	HVLA	7.56	4	3.33	8	absurdo (absurd)	LVLA	4.08	4.53	28.19	7
16	afecto (affection)	HVLA	8.14	4.21	21.28	6	áspero (rough)	LVLA	3.45	4.69	10.24	6
17	beleza (beauty)	HVLA	7.46	4.25	68.29	6	bastardo (bastard)	LVLA	3.93	4.03	3.33	8
18	bonito (handsome)	HVLA	7.4	4.36	92.04	6	débil (feeble)	LVLA	3	4.86	6.66	5
19	elegante (elegante)	HVLA	6.76	4.33	18.44	8	desculpa (excuse)	LVLA	4.89	4.34	26.71	8
20	ídolo (idol)	HVLA	6.08	4.57	5.68	5	distante (aloof)	LVLA	3.25	4.44	39.17	8
21	inspirar (inspire)	HVLA	7	4.27	29.73	8	hábito (habit)	LVLA	5.08	3.09	63.72	6
22	memória (memory)	HVLA	6.12	4.33	105.06	7	mutação (mutation)	LVLA	4.49	4.58	7.77	7
23	nutrir (nourish)	HVLA	6.21	3.89	6.54	6	obedecer (obey)	LVLA	4.73	4.93	32.82	8
24	riqueza (riches)	HVLA	6.82	4.51	53.85	7	sério (serious)	LVLA	4.84	4.05	88.77	5
25	sábio (wise)	HVLA	7.27	3.71	18.2	5	solidão (loneliness)	LVLA	2.1	4.78	36.52	7
26	seguro (safe)	HVLA	7.09	3.09	83.34	6	solitário (lonely)	LVLA	2.71	3.95	19.12	9
27	vigoroso (vigorous)	HVLA	6.31	4.7	9.62	8	tímido (timid)	LVLA	4.29	3.85	16.72	6
28	virtude (virtue)	HVLA	7.29	3.38	42.57	7	virgem (virgin)	LVLA	4.98	4.15	12.15	6
		TOTAL	**6.97**	**4.11**	**39.86**	**6.64**		**TOTAL**	**3.99**	**4.31**	**27.99**	**6.86**

Note. HV=High Valence, HA=High Arousal, LV = Low Valence, LA = Low Arousal