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Semantic projection as a method to measure individual differences in semantic scale length: insights from autism-related traits

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Human perceive and navigate the world using internal scales constructed for various semantic features (e.g., danger, weight), and these scales vary considerably in length and endpoints among individuals. Quantifying these scale lengths is critical for understanding cognitive diversity, yet existing methods face reliability challenges. Here, we extend Grand et al.'s semantic projection approach through a free-response paradigm to measure individual differences in scale length. Applying this framework to autistic traits, we uncover a dissociation: in male participants, those with high Autism-Spectrum Quotient (AQ) scores exhibited significantly shorter scale lengths for abstract features compared to low-AQ males, revealing compressed conceptual representations in neurodivergent cognition. In contrast, no such differences were observed among females or for physical features. Potential implications and accounts are discussed.

Keywords Semantic conception, Semantic projection, Word embedding, Autism, Gender difference

Human perception and decision-making are profoundly shaped by our prior knowledge about the characteristic features of different objects and categories[1–3]. For instance, many people judge snakes to be "dangerous" in terms of the feature "danger", drawing on their previous experiences or cultural associations; as a result, they tend to avoid encounters with snakes. A given feature, such as danger, can be conceptualized as a continuous dimension defined by antonymous adjective pairs (e.g., "safe" and "dangerous"), as described in previous studies[4,5]. Every object or event can be subjectively located somewhere along this continuum, enabling systematic measurements of our perceptions of various concepts along different feature dimensions.

Using such measurements, group consensus regarding the features of objects can be quantified; for example, on a 7-point "safe" to "dangerous" scale, snakes might receive an average danger rating of 5.1. To make this consensus meaningful, it is generally assumed that all participants are using the same underlying psychological scale. However, in reality, each individual's internal metric—for instance, their personal interpretation of the "safe–dangerous" or "light–heavy" continuum—may differ in length and endpoints[4,6–8].

Despite this recognition, directly measuring the scale length at the individual level remains a significant challenge. Operationally, an individual's "scale length" for a feature such as danger can be defined as the subjective distance between what they consider to be the most dangerous and the safest entities[4,6,8,9]. Within this framework, the subjective evaluation of any given object's danger is referenced against these personal anchors, and the full range of perceived danger for each individual falls within this personally defined interval. However, operationalizing these endpoints poses a fundamental methodological constraint: While concrete features like size could ostensibly be anchored by physical measurements, such approaches conflate perceptual scaling with objective reality. Crucially, they fail entirely for abstract features (e.g., danger), where endpoints are socio-linguistic constructs rather than physical observables. Even for physical features, human knowledge integrates social categories—consider how "large" a house is judged not by square footage alone, but by neighborhood prestige—rendering purely physical anchors inadequate.

To overcome this limitation, combining with free response paradigm, we leverage distributional semantic knowledge embedded in pre-trained Word2Vec models—trained on vast corpora reflecting collective human experience—to derive individual-level scale lengths via semantic projection[5].

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Semantic projection: From collective knowledge to individual differences. Human knowledge is deeply embedded in language. Word embeddings, trained on large corpora of human-generated text, represent words as high-dimensional vectors that capture semantic relationships. While the individual dimensions of these vectors are typically not human-interpretable, the geometric structure of the embedding space robustly reflects semantic associations analogous to those in human cognition[5,10–12]. In this sense, word embeddings can be viewed as encoding statistical regularities derived from collective human linguistic experience.

Building on word embeddings, Grand et al. established semantic projection: By defining axes between vectors of antonym adjective pairs (e.g., {dangerous, deadly, threatening} → {safe, harmless, calm} for the feature "danger"), projecting word vectors onto these axes yields feature similarity scores that correlate strongly with human judgments[5]. Critically, their work validated this approach for recovering the rich human knowledge in word embeddings. Here, we extend this framework through a free-response paradigm to construct the individual-level scale length of different features. Participants first generate their personal endpoint exemplars (e.g., "the most dangerous/safest things I can imagine") without constraint. We then project these responses into a unified semantic space using pre-trained Word2Vec models, deriving individual scale lengths as distances between projections of these extreme concepts. This hybrid approach quantifies subjective scaling while preserving real-world conceptual diversity. As a rigorous test of this framework, we conduct systematic comparisons across the autistic trait continuum—an individual-difference dimension where socio-perceptual scaling differences are theoretically salient yet methodologically unquantified[13–16].

Scale length of different features in population with autistic traits. A central observation about Autism Spectrum Disorder (ASD) is that autistic individuals tend to perceive the world differently[14,17,18]. Their perceptual processing is often characterized by a heightened focus on local features over global structure, commonly referred to as "seeing the trees, but not the forest"[18–20]. Such detail-focused and less flexible perceptual style has been observed not only in clinically diagnosed individuals but also along the broader autistic trait continuum. For instance, evidence has shown that questionnaire-based measures of sensory sensitivities covary with autistic traits in the general population[18,21]; individuals scoring high on the Autism-Spectrum Quotient (AQ) in a visual signal detection task were found to be less influenced by base-rate priors than their low-AQ peers[22]; and those with high autistic traits perceived fewer reversals of ambiguous figures than those with low traits[23]. Together, these findings suggest that atypical perceptual styles extend beyond clinical ASD to individuals with elevated autistic traits in the general population.

This perceptual style has been explained by various theoretical accounts, including the Bayesian framework[13,14], the predictive processing framework[16,24], and the enhanced perceptual functioning model[25,26]. While these accounts differ in emphasis, they converge on the notion of atypical feature construction in autism—particularly for abstract features (e.g., intelligence), which rely heavily on social experience and prior knowledge. Crucially, "pre-existing priors" (knowledge that individuals have before receiving any task-relevant information) appear largely intact for physical features in autism[13]. For instance, prior knowledge regarding geometrical shapes, line orientations, continuation of motion, direction of light and colors of natural scenes were similar across diagnostic groups and autistic traits according to previous studies[13,27–32]. However, for social priors such as social images (for instance, Mooney images containing at least one person) and biological motion (although it may not represent a purely social prior), which is highly relevant for ASD, the evidence was relatively mixed compared with physical priors[13,33,34]. This dissociation raises the possibility that the internal scaling of physical features remains stable in individuals with autistic traits, whereas the representation or construction of abstract/social features may follow atypical patterns.

Also relevant to feature construction in autism, category processing in ASD has been shown to differ from that of controls. Early work demonstrated that across childhood, adolescence, and adulthood, autistic participants were disproportionately slower than controls to verify atypical category members, despite both groups exhibiting a typicality effect[35]. Similar difficulties have been observed in implicit category formation with dot-pattern prototypes[36], in the learning of novel relational categories among children with ASD[37], and in word-extension paradigms that require inferring narrow category boundaries from social-pragmatic cues[38]. Although such findings in ASD may not directly generalize to the broader population with high autistic traits, evidence from category processing nonetheless suggests that feature construction varies with autistic traits.

Moreover, gender differences may also influence how autistic individuals conceptualize both physical and abstract features. Although a recent large-scale study found no significant sex differences among autistic toddlers[39], previous research had consistently shown that female autistic adults tend to exhibit better social functioning and fewer restricted or repetitive behaviors[40–42], which partly explains why autistic females are often harder to diagnose. In the general population, study had found that both low- and high-AQ women showed a significant positive association between autistic traits and camouflaging, indicating that higher levels of traits were linked to greater use of strategies to mask or compensate for autism-related social and behavioral features[43]. Among men, however, this relationship was evident only in the high-AQ group, but not in the low-AQ group. This suggests that the relationship between autistic traits and camouflaging may be more consistent among women, whereas for men the pattern appears less stable, potentially reflecting additional social or cultural factors.

Against this background, in the current study, we aim to systematically evaluate how individuals across the autistic trait spectrum conceptualize both physical and abstract features by constructing participant-level feature scales using semantic projection. Based on previous studies, we hypothesize that the scaling of physical features (e.g., weight) will not significantly differ between individuals with low and high autistic traits. However, for abstract features (e.g., intelligence), we expect to observe significant differences in feature scaling between these groups—particularly among males compared to females. Figure 1 presents an overview of the main procedure.

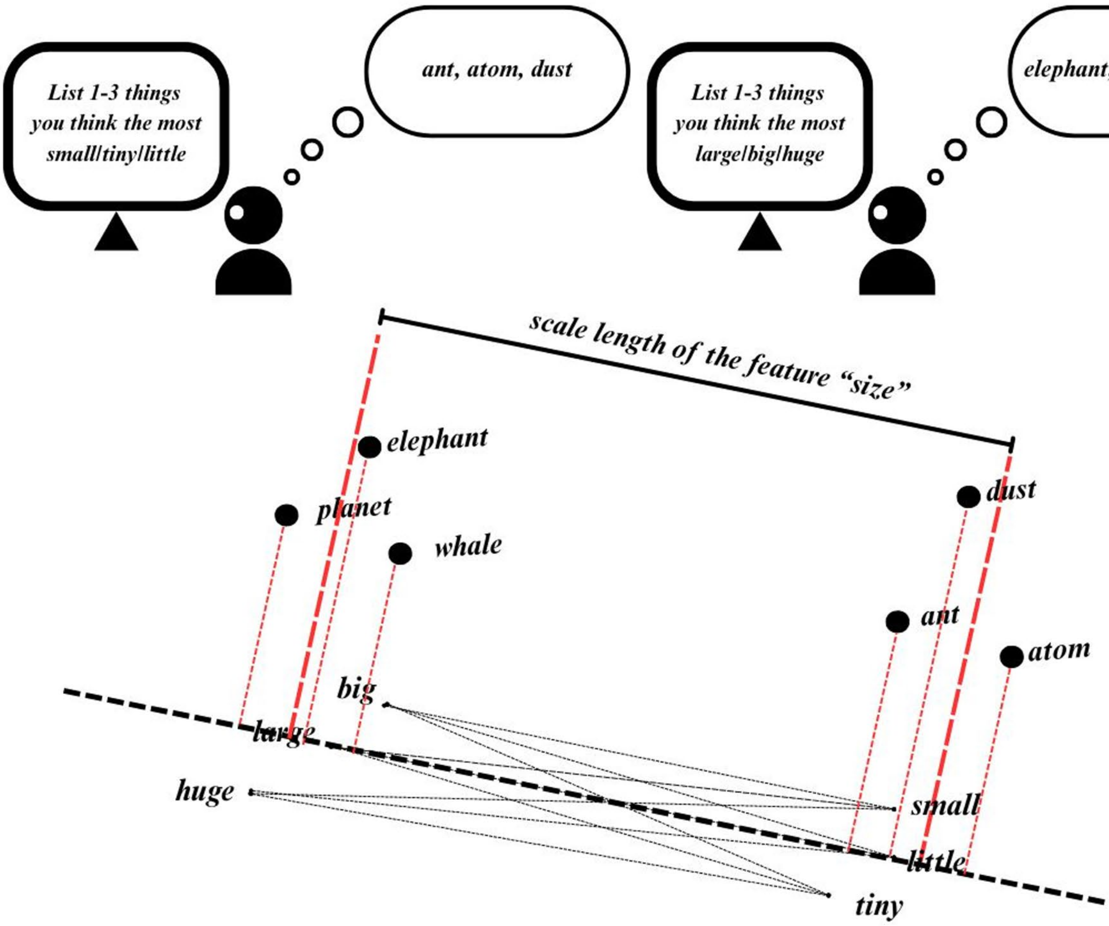

Fig. 1. An illustration of the current study. The semantic projection was visualized in 2D space for clarity and better visualization, though no dimensionality reduction was applied in the actual analysis.

Method

Participants

105 participants (44 male and 61 female, age:18–30) were recruited through campus posters. All participants were native Chinese college students and completed the experiment online. Informed consent was obtained from all participants, who received 20–25 yuan as compensation for their participation.

Procedure

The experiment was conducted online using jsPsych[44]. Participants completed a series of 40 free-response questions designed to establish individual-level feature scales. For each of 20 semantic features (e.g., size), participants answered two anchor-point questions in Chinese: "list one to three things you think the most big/huge/large" and "list one to three things you think the most small/little/tiny". The dimensions were presented in a randomized order, and the anchor-point questions were also randomized within each dimension. The whole procedure required approximately 25–35 min to complete.

Autistic traits were assessed using the 50-item Autism-Spectrum Quotient (AQ) questionnaire[45]. The AQ demonstrates established reliability in measuring autistic traits across clinical and non-clinical populations[46–48].

Feature selection

We defined physical features as those quantifiable via instruments or direct sensory perception (e.g., size with a ruler, weight with a scale, temperature with a thermometer, speed with a radar gun), while abstract features were defined as those requiring human judgment, cultural context, or emotional interpretation (e.g., cost, intelligence, arousal, valence, danger), the definition was congruent with the standards in previous studies[49,50]. We adopted 12 features from Grand et al.[5] and introduced 6 novel physical features and 2 novel abstract features, resulting in a total of 12 physical and 8 abstract features in current study. Each feature was operationalized using 2–3 antonymous adjective pairs defining scale endpoints. Critically, our classification demonstrated strong alignment with Binder et al.'s taxonomy[49]: when classification was applied at the dimension level, 7 of the 12 physical feature dimensions corresponded to Physical Property super-category terms, and 6 of the 8 abstract feature dimensions mapped to Abstract Property super-category terms. For adjectives absent in Binder et al.'s taxonomy, experimenters achieved complete consensus in physical/abstract classification based on the original framework's definitions. Feature with their corresponding antonymous adjective pairs could be found in https://osf.io/5k9uq/.

Model selection and semantic projection

Pre-trained Chinese Word2Vec embeddings trained on a combined corpus with both words and bigrams as training contexts were employed in the current study[51]. This model was trained by Li et al.[51] using a combination of six corpora: Chinese Wikipedia, Baidu-baike (an online Chinese encyclopedia), Zhihu (Chinese social QA data), People's Daily News, Sogou News, and Financial News. We selected this model following Li et al.'s CA8 benchmark: the mixed-domain "Combination" corpus yields the strongest overall results (under SGNS-word), and adding word bigrams (word + ngram) improves SGNS over word-only; our setup follows these findings (models could be downloaded at https://github.com/Embedding/Chinese-Word-Vectors).

For each feature, a semantic subspace was defined by averaging pairwise vector differences between antonyms, as in Grand et al.[5]. For example, the "size" subspace was derived by averaging all vector differences between {large, big, huge} and {small, little, tiny} ($3\times3=9$ combinations). For a feature subspace $\vec{d}$ with N antonymous adjective pairs, we define:

$$\vec{d}_{feature} = \frac{1}{N^2}\sum\nolimits_{i=1}^{N}\sum\nolimits_{j=1}^{N}\left(\vec{a}_i - \vec{b}_j\right)$$

where $\vec{a}_i$ is the word vector of the *i*-th word at one end of the feature (e.g., "big", "large", "huge"), and $\vec{b}_j$ is the word vector of the *j*-th word at the opposite end (e.g., "small", "little", "tiny").

Participants' responses were standardized to the Word2Vec vocabulary. Invalid entries, such as proper nouns and responses identical to the given adjectives, were excluded. Each participant's answers were converted to Word2Vec vectors and projected onto the fixed feature subspace; the formula represents as follows:

$$Projection\ (\vec{w}) = \frac{\vec{w}\ \bullet\ \vec{d}_{feature}}{\|\ \vec{d}_{feature}\ \|}$$

While Grand et al. used the dot product between the target word vector and the feature subspace vector, we additionally divided the dot product by the norm of the feature vector which enables better comparability of projection scores across different features. The participant-level feature scale length was calculated as the distance between the mean projections of their responses on the two sides of the feature. For example, if a participant listed "lava" (projection: +0.7) and "desert" (projection: +0.6) for hottest, and "glacier" (projection: −0.7) and "ice" (projection: −0.8) for coldest, the scale length would be $(0.7+0.6)/2 - (-0.7-0.8)/2 = 1.4$.

Analyses

A strict participants exclusion criterion was used due to the uncertainty in online experiment. The participants will be excluded from the formal analyses if their answers are overlapped with more than 10% of the antonymous adjectives in current study. The participants were then divided into two groups based on their AQ scores: the low AQ group (AQ ≤ median) and the high AQ group (AQ > median).

Since both the number of answers and scale length may be influenced by AQ group, generalized linear mixed-effects model (GLMM) with a Poisson distribution and a log link function was fitted to predict the number of answers and linear mixed-effects model (LMM) for scale length, respectively. The number of answers was calculated for each feature (i.e., one value per feature for each participant). Analyses were conducted using the *lme4* package[52] in R[53]. The initial maximal models included random slopes for fixed effects but was simplified to random intercepts for participants and features only due to singular fit warnings. The final models included fixed effects for gender (male vs. female), group (low-AQ vs. high-AQ), feature type (physical vs. abstract), all their two-way and three-way interactions, and age as a grand-mean-centered covariate, with random intercepts for participants and features. P-values were derived using Satterthwaite's approximation via the *lmerTest* package[54], specified as: Number of answers ~ gender * group * feature type + age + (1 | participant) + (1 | feature), Scale length ~ gender * group * feature type + age + (1 | participant) + (1 | feature). In the GLMM for the number of answers, the variable age was scaled (centered and standardized) to improve model convergence. All post-hoc pairwise comparisons were performed using the *emmeans* package[55]. The decision to use AQ group as a fixed effect instead of raw AQ scores was made for better clarity of presentation. Results from LMM fitted with raw AQ scores were also provided in OSF and were highly similar to those obtained using group as a fixed effect.

To test the robustness of the results, we conducted an additional analysis after excluding extreme words on each endpoint of each dimension. Specifically, for each endpoint of each dimension, words exceeding ± 2.5 SD from the mean were excluded from subsequent analyses. The same linear mixed-effects model, Scale length ~ gender * group * feature type + age + (1 | participant) + (1 | feature), was then fitted to the data following outlier exclusion.

Result

Three participants were excluded due to incomplete data, and six were excluded based on strict criteria (i.e., their responses overlapped with more than 10% of the given antonymous adjectives). The final sample included 96 participants (43 males, 53 females; age range: 18–30 years). The mean AQ score among these participants was 20.22. Based on the median AQ score of 20, 45 participants were assigned to the high AQ group (22 female) and 51 to the low AQ group (31 female). The distribution of AQ scores by gender was shown in Fig. 2.

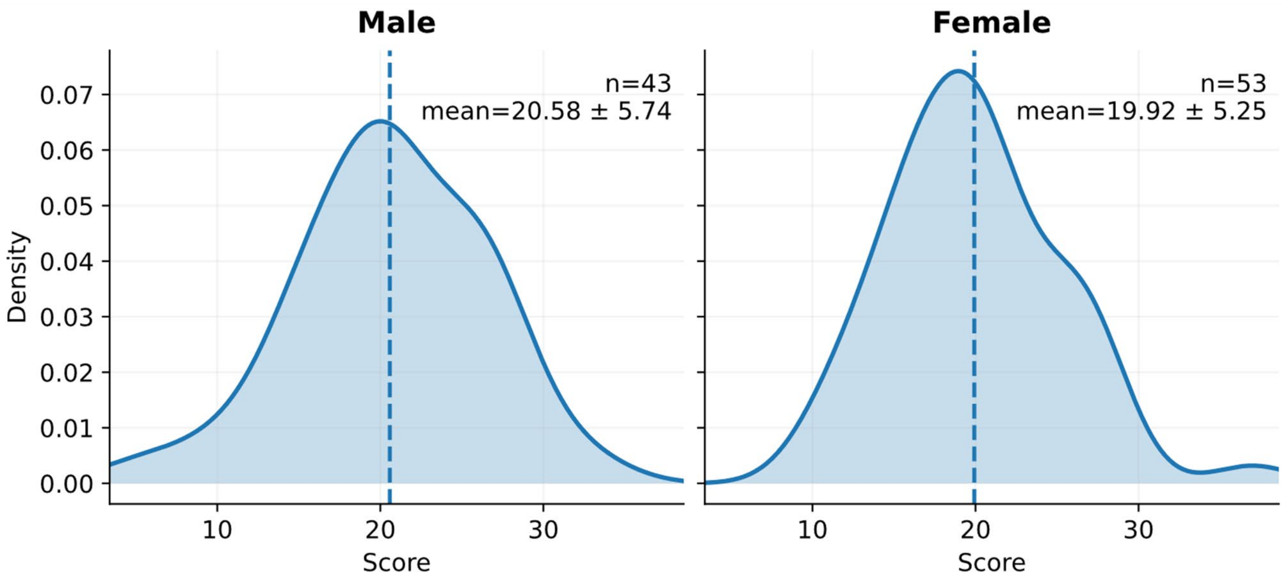

Fig. 2. The distribution of AQ scores by gender. Curves show Gaussian kernel density estimates (Scott's bandwidth); areas integrate to 1. Dashed lines indicate group mean.

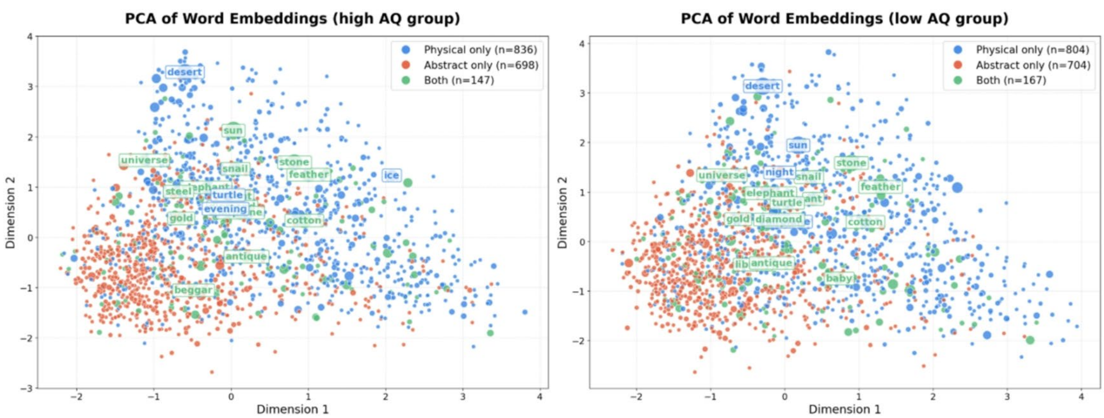

Fig. 3. Distribution of low- and high-AQ participants' responses in the semantic vector space, projected onto two dimensions using principal component analysis (PCA). The words displayed are high-frequency responses (top 1%), translated from Chinese. "Both" indicates words that were used as responses for both physical and abstract features. The size of each dot represents the frequency with which a word appeared.

Number of answers. In total, 8,124 words were collected, with 4,899 corresponding to physical features and 3,245 to abstract features. The distribution (4,899 vs. 3,245) is consistent with the study design, given that the number of physical features was 1.5 times greater than that of abstract features. Of the collected words, 453 were not present in the word embedding vocabulary and were excluded from further analysis, yielding a final set of 7,671 words. Each participant provided between 34 and 120 valid words. At the dimension level, the number of valid words per participant ranged from 0 to 8. When a participant provided too few valid words to calculate the scale length for a given dimension, the corresponding scale length for that dimension was not calculated. On average, each participant provided 4.09 valid words for each physical feature and 3.85 valid words for each abstract feature. Although there were negative trends, neither the total number of answers ($r = -0.158$, $p = 0.124$) nor the number of valid answers ($r = -0.161$, $p = 0.116$) was significantly correlated with AQ scores. The distribution of participants' responses in the two-dimensional semantic vector space is shown in Fig. 3.

The GLMM for the total number of answers (i.e., all responses irrespective of validity) revealed a marginal effect of gender ($\beta = -0.185$, $SE = 0.103$, $z = -1.79$, $p = 0.074$), which did not reach conventional levels of statistical significance. No other significant effect or interaction was observed, including the interaction between AQ group and gender ($\beta = 0.21$, $SE = 0.143$, $z = 1.475$, $p = 0.140$) and the three-way interaction AQ group × gender × feature type ($\beta = -0.063$, $SE = 0.095$, $z = -0.657$, $p = 0.512$).

Scale length. The scale length pattern in each feature was plotted in Fig. 4. The LMM for scale length revealed a significant interaction between AQ group and gender ($\beta = 0.226$, $SE = 0.097$, $t = 2.322$, $p = 0.021$). Additionally,

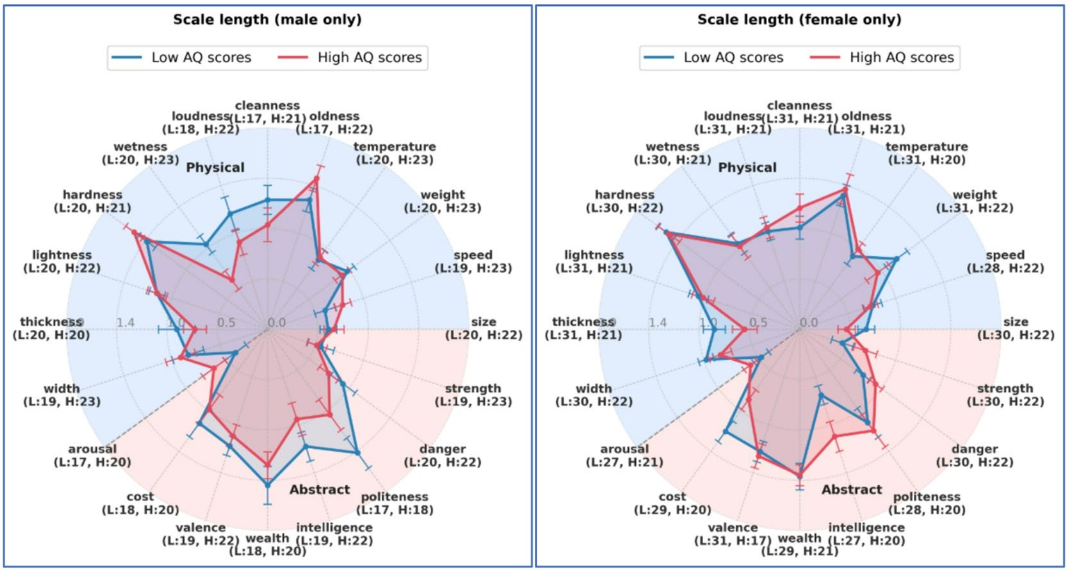

Fig. 4. Mean scale length for each feature in low and high AQ groups separated by gender.

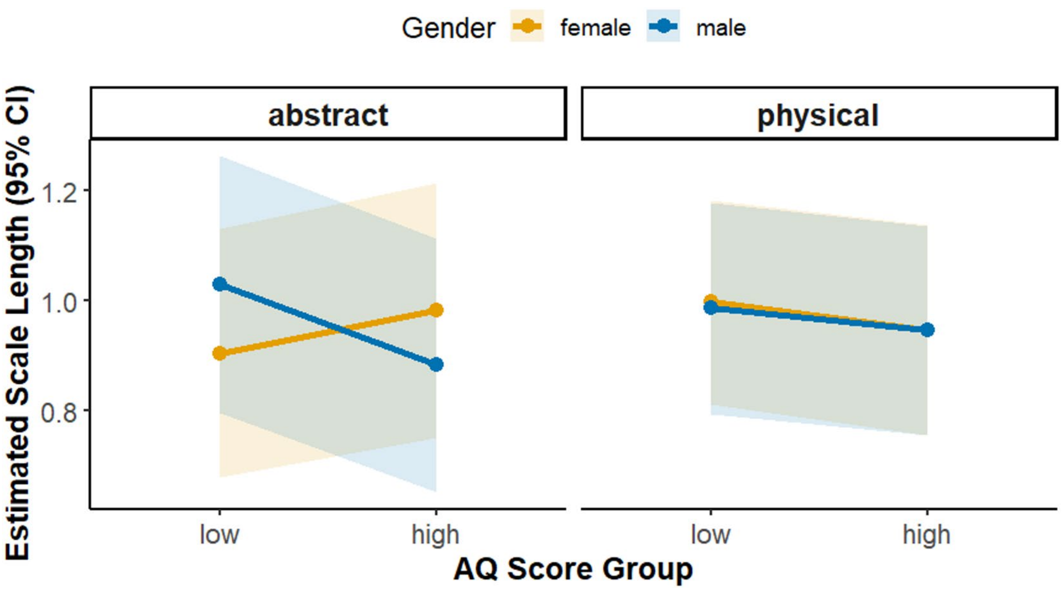

Fig. 5. Interaction between AQ group and gender in estimated scale length (with 95% CI), separated by feature type.

the LMM revealed a three-way interaction of AQ group × gender × feature type (β = −0.236, SE = 0.107, t = −2.205, p = 0.028). The interaction between AQ group and feature type (β = 0.13, SE = 0.072, t = 1.815, p = 0.07) approached significance, no other significant effect was observed.

To further investigate the significant three-way interaction among group, type, and gender, we conducted simple effects analyses using pairwise comparisons of AQ group (high vs. low) within each combination of feature type and gender. The results showed that a significant difference between the high and low groups was only found for males performing abstract tasks (*estimate* = −0.146, p = 0.043), with the high AQ group showing a shorter scale length than the low AQ group. No significant group differences were observed in any other type-gender combinations (all $p > 0.05$). Estimated marginal means of scale length for each combination of AQ group, gender, and feature type are plotted in Fig. 5.

Scale length after outlier exclusion. Among the 7,671 valid words, a total of 126 words were excluded from further analysis based on the ± 2.5 SD criterion, corresponding to an average of 6.3 words per dimension. The LMM for scale length after outlier exclusion closely mirrored the results obtained without outlier exclusion. Specifically, we observed a significant interaction between AQ group and gender (β = 0.215, SE = 0.089, t = 2.419,

$p = 0.016$), as well as a significant three-way interaction of AQ group × gender × feature type ($\beta = -0.225$, $SE = 0.100$, $t = -2.232$, $p = 0.026$). These findings indicate that the significant effects reported above were not driven by outliers, thereby supporting the robustness of the results.

Discussion

Human knowledge is largely embedded in linguistic corpora, and word embeddings trained on such corpora are capable of capturing this collective semantic information. Given a sufficiently large and representative corpus, word embeddings can generally approximate socially shared semantic knowledge, although the accuracy of this approximation is influenced by the choice of model architecture and training procedures. Consequently, individually generated responses can be positioned within this semantic vector space, enabling quantitative assessment of their locations within a multidimensional semantic continuum. Such analyses potentially provide insights into individuals' conceptual understanding, reflecting their internal semantic representations of specific concepts.

Understanding these individual semantic representations is of vital importance, as we perceive and navigate the world using internal scales constructed for various semantic features, and these scales vary in length among individuals. The current study aimed to develop a novel method for constructing individual-level feature scales by combining semantic projection with free-response paradigm. Using this approach, we observed significant differences in scale lengths between high and low AQ groups specifically among males for abstract features; notably, the high AQ group exhibited significantly shorter scale lengths compared to the low AQ group. These findings align with previous research suggesting that priors related to physical features may be relatively intact in individuals with ASD, whereas priors involved in more abstract, socially relevant processing show mixed evidence[13].

Moreover, our results are consistent with studies highlighting significant gender differences among individuals with autism[40–42]. The unimpaired scale length observed in high-AQ females may help explain the delayed or missed diagnoses in this group, as the priors they rely on for observation and decision-making do not appear to differ significantly between AQ groups. However, whether these relatively unimpaired priors in high-AQ females contribute to less restricted and repetitive behavior, or whether less impaired behavior leads to the preservation of such priors, remains to be further investigated.

For the concerns regarding the representativeness of the sample, we compared the AQ results of our sample with published norms. Specifically, we searched for recent studies using the same AQ measure with Chinese participants and found highly comparable distributions[56,57]. For example, one study reported a median of 21 and a mean of 21.17 ± 7.1[56], while our sample showed a median of 20 and a mean of 20.22 ± 5.42, suggesting that our sample is representative. Besides these results, the present study also provides a large dataset of free responses from different AQ groups, which may serve as a valuable resource for further investigation by researchers interested in this area.

Limitations. As could be seen in the OSF materials, a few semantic projections were somewhat counterintuitive and did not necessarily reflect widely shared social consensus. These anomalies may stem from biases inherent in the training corpora, limited representational accuracy of word embeddings, or subtle variations in semantic associations across different contexts or populations. In addition, word embedding models are not always sensitive to antonymy relations, whereas such relations may be better captured by large language models (LLMs). This represents a potential limitation of the present study, and future work could explore alternative approaches, for instance by employing contextual embeddings rather than static word embeddings. Moreover, it is important to note that not all pre-trained Word2Vec models yield identical or equally reliable projections; the quality of semantic projections can significantly vary depending on the choice of training corpora, embedding algorithms, and parameter settings. In the current study, we selected a well-established Word2Vec model[51], thus mitigating these concerns to some extent. Additionally, cross-linguistic differences in word embeddings represent a further limitation, as Chinese word embeddings do not always perform comparably to those in other languages. As a promising future direction, word-association embeddings could be considered, given their demonstrated advantages over text-based embeddings in various tasks[58]. Also, our free-response paradigm differs from that of Grand et al., where exemplars were scaled within the context of a semantic category (e.g., dolphin, crocodile: how dangerous for the category of mammals). Such context-dependent responses may yield more precise effects by constraining responses within a specific category, and thus represent a valuable direction for future research. Another limitation is that some participants may have had undiagnosed autism, which could have influenced the current results. While such individuals might present AQ scores comparable to those of the typical high-AQ population, their responses could differ in ways from those without a clinical condition. Future studies are needed to further investigate this possibility.

Data availability

Participants' free responses and data supporting the findings of this study can be found in OSF: https://osf.io/5k9uq/.

Code Availability

Codes for semantic projection and other codes supporting the findings of this study can be found in OSF: https://osf.io/5k9uq/.

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Declarations

Competing interests
The authors declare no competing interests.

Ethical approval
This study has been reviewed and approved by the Ethics Committee of Beijing Language and Culture University (Approval No.: 2025BYLL55). All methods were performed in accordance with the relevant guidelines and regulations.

Additional information

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