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The conceptual structure of human relationships across modern and historical cultures

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Xi Cheng[1,9], Haroon Popal[1,2,9], Huanqing Wang[1,9], Renfen Hu[3], Yinyin Zang[4], Mingzhe Zhang[1], Mark A. Thornton[5], Yina Ma[1], Huajian Cai[6], Yanchao Bi[1], Jamie Reilly[7], Ingrid R. Olson[8] & Yin Wang[1] ✉

A defining characteristic of social complexity in *Homo sapiens* is the diversity of our relationships. We build connections of various types in our families, workplaces, neighbourhoods and online communities. How do we make sense of such complex systems of human relationships? The basic organization of relationships has long been studied in the social sciences, but no consensus has been reached. Here, by using online surveys, laboratory cognitive tasks and natural language processing in diverse modern cultures across the world ($n = 20{,}427$) and ancient cultures spanning 3,000 years of history, we examined universality and cultural variability in the ways that people conceptualize relationships. We discovered a universal representational space for relationship concepts, comprising five principal dimensions (formality, activeness, valence, exchange and equality) and three core categories (hostile, public and private relationships). Our work reveals the fundamental cognitive constructs and cultural principles of human relationship knowledge and advances our understanding of human sociality.

No man is an island. Human life is a process of seeking, sustaining, repairing, judging, adjusting and sometimes dissolving relationships[1]. The quality and quantity of relationships are integral not only to our survival but also to our capacity to thrive[2,3]. Social isolation and poor relationships affect an individual's cognition, behaviour, development and well-being[4,5].

Understanding the nature of human relationships lies at the heart of the social sciences. However, studying relationships is challenging for several reasons. First, human relationships are characterized by their diversity and complexity. Social structure in non-human primates is largely dominated by hierarchy and affiliation[6]. Human society, in contrast, is governed by far more diverse and complex types of relationships (for example, frenemies, godparents and online friends). Human relationships are also context-dependent and multifaceted, involving numerous factors such as time, space, emotions, communication and cultural norms[7]. These factors interact with one another in intricate ways, making it difficult to isolate and study individual components. Unravelling the underlying elements and organizational structures of such a complex relationship system thus remains a vexing problem.

Second, human relationships are subjective beliefs, experiences and practices shaped by the unique perspectives, attitudes and personalities of the individuals involved and maintained by dynamic, unwritten rules over time and across societies[8]. This subjectivity makes

[1]State Key Laboratory of Cognitive Neuroscience and Learning, and IDG/McGovern Institute for Brain Research, Beijing Normal University, Beijing, China. [2]Department of Psychology, University of Maryland, College Park, MD, USA. [3]School of International Chinese Language Education, Beijing Normal University, Beijing, China. [4]School of Psychological and Cognitive Sciences and Beijing Key Laboratory of Behavior and Mental Health, Peking University, Beijing, China. [5]Psychological and Brain Sciences, Dartmouth College, Hanover, NH, USA. [6]Department of Psychology, University of Oklahoma, Norman, OK, USA. [7]Department of Communication Sciences & Disorders, Temple University, Philadelphia, PA, USA. [8]Department of Psychology and Neuroscience, Temple University, Philadelphia, PA, USA. [9]These authors contributed equally: Xi Cheng, Haroon Popal, Huanqing Wang. ✉e-mail: mirrorneuronwang@gmail.com

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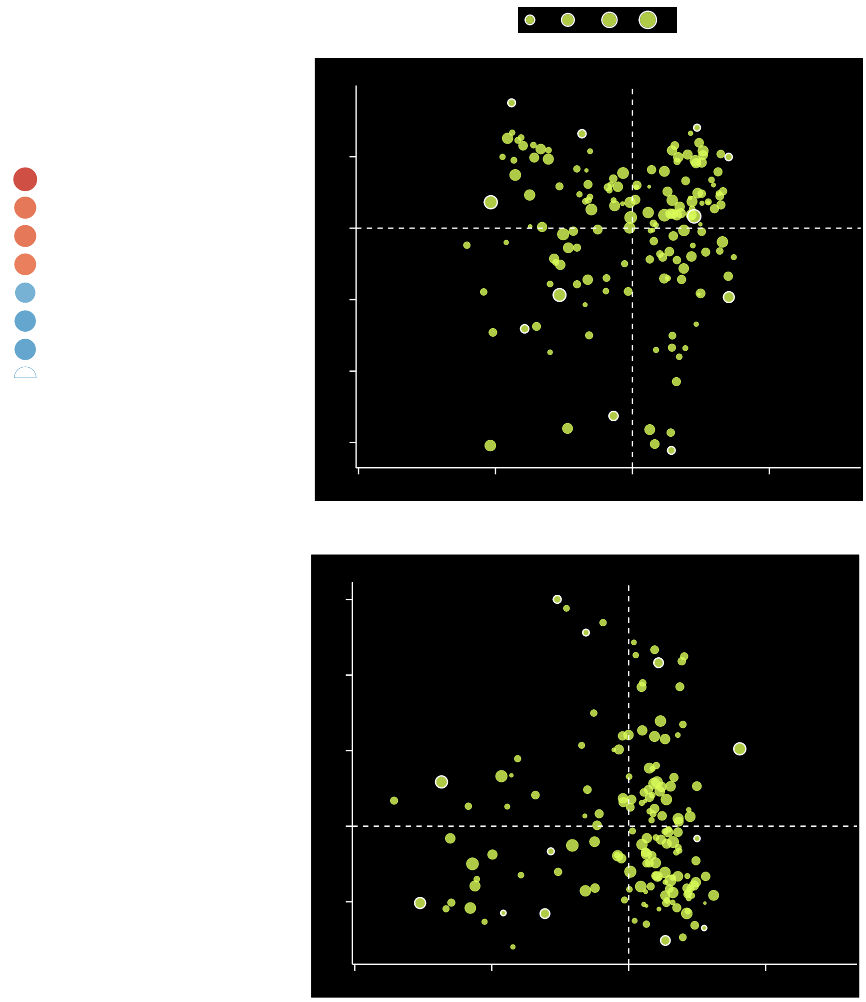
orthogonalized latent factors via principal component analysis (PCA). The PCA extracted five latent dimensions, accounting for 82.14% of the variance of dimensionality ratings (see Methods and statistics on how to determine the optimal PCA component number). On the basis of close examination of the PCA loadings and relationship scores (Fig. 1), the first dimension was identified as 'formality'. This dimension contrasts formal, occupational and publicly visible relationships that adhere to rules and regulations (for example, co-workers and officer–soldier) with informal, socio-emotional and private relationships that exhibit a looser, more casual style (for example, parent–infant and wife–husband). The second dimension, which we termed 'activeness', loaded highly on activeness, synchronicity and spatial distance. Close relationships (for example, wife–husband and siblings) and distant relationships (for example, distant relatives and strangers) occupied the poles of this dimension. The third dimension was described as 'valence', with friendly, harmonious and high-solidarity relationships at one pole (for example, church members and writer–reader) and conflictual, hostile and antagonistic relationships at the other (for example, bully–victim and slave–master). We named the fourth dimension 'exchange', as it distinguishes between dyads exchanging concrete resources such as money, goods and services (for example, dealer–buyer and prostitute–customer) and dyads exchanging symbolic, intangible resources such as information, love and identity (for example, celebrity–haters and brother–sister). The fifth dimension was labelled 'equality', as it differentiated dyads with equal powers (for example, sports rivals and pen friends) from dyads with unequal powers (for example, man–god and politician–supporter). Other dimensionality reduction techniques (that is, independent component analysis, exploratory factor analysis and multidimensional scaling) were also evaluated to examine the robustness of the latent factor solution to different statistical algorithms, and they all yielded the same five-factor solution (Supplementary Fig. 3). We hereafter refer to this five-dimensional solution as the FAVEE model (an abbreviation for formality, activeness, valence, exchange and equality).

Categorical thinking (for example, family, friends and colleagues) is pervasive when people define and manage their social connections. We next studied how people sort relationships and how categorical representations relate to the FAVEE dimensions. Two cognitive paradigms were employed: in the multi-arrangement task[12], participants judged the similarity between the 159 relationships by arranging them on a 2D computer screen in such a way that the distance between any two relationships reflected their conceptual dissimilarity (that is, the more conceptually similar, the closer together the relationships were); in the free sorting task[13], participants classified the same set of relationships into labelled categories of their choosing.

Using a within-subject design, we recruited 60 US participants to complete three tasks in the laboratory (that is, one dimensional survey and two cognitive tasks) (Fig. 2a). Categorical representations were derived from each task by applying clustering algorithms to the dissimilarity matrix of relationship concepts. Three clusters were found in the dimensional survey, which can be labelled 'hostile, private and public' (abbreviated as the HPP model) (for optimal cluster details, see Methods). Relationships in the 'hostile' cluster featured people who are antagonistic or have negative feelings with each other, such as 'divorced spouses' and 'business rivals'. Relationships in the 'private' cluster were personal and family ties, such as 'siblings' and 'close friends'. Relationships in the 'public' cluster were formal and occupational and had impersonal ties, such as 'driver–passenger' and 'employer–employee'. In contrast, clustering on the two cognitive tasks revealed six canonical relationship types: hostile, familial, romantic, affiliative, transactional and power. Text analysis on the labels during the free sorting task further revealed that six canonical types emerged from three HPP categories (Fig. 2b): while the hostile cluster in the HPP model remained, the private cluster was divided into three distinct



cluster was split into two classes (transactional and power relationships). To further clarify the associations between the FAVEE and HPP models, a dimension–category hybrid representation was evaluated where clustering techniques were applied to the relationships in the FAVEE embedding space. Again, three HPP clusters were identified (Fig. 2c), and each was embedded in a unique location in the 5D space: the private and public clusters were located separately at the two ends of the formality dimension, and the relationships that were low on the valence dimension formed the hostile cluster. This implied that HPP categories could originate from the FAVEE dimensions.

In sum, Study 1 revealed that when people think about social relationships, they attend to five key features. We demonstrated that all relationship concepts are mentally represented in a high-order FAVEE space, and the conceptual similarity between each pair of relationships can be represented as the distance in the 5D space. Once the spatial proximity among relationships is close enough along certain featural dimensions, they can be self-clustered into meaningful categories (for example, three HPP clusters or six canonical types). Relationship categories thus emerge from uneven distributions along the FAVEE dimensions, and relationship taxonomies can be understood as discrete sets of categories living in a continuous multidimensional space (see an illustrative flow chart in Fig. 2d).

Study 2: universality and variability across modern cultures

All human cultures have rich vocabularies devoted to describing human relationships. Translation dictionaries, for example, suggest that the English word 'neighbours' can be equated with the Chinese word ' ' and the Hebrew word ' '. However, does this mean that the concept of 'neighbours' is the same in the USA, China and Israel? In Study 2, we explored this question by examining representations of relationship concepts across 19 global regions and 10 languages. We aimed to reveal the cross-cultural similarity and differences and their underlying cultural mechanisms.

Study 2 was preregistered on the Open Science Framework (https://osf.io/swr2c) on 13 June 2022. We report deviations from preregistration in Supplementary Method 3. A large sample of online participants (n = 17,686) were recruited from 19 global regions with diverse ecological (geography, climate and subsistence), biological (genetics and disease prevalence) and sociocultural backgrounds (language, ethnicity, education, religion, politics, wealth and urbanization) (see Supplementary Fig. 13 for the details). The dimensional survey approach was adopted due to its higher within-culture stability over cognitive tasks (Supplementary Fig. 2). For each region, three types of representational geometries were generated on the basis of representational dissimilarity matrices (RDMs)[14,15]: the full-feature model (that is, RDMs based on the original data on all evaluative features without applying any dimensionality reduction or clustering techniques), a dimensional model (that is, RDMs based on FAVEE) and a categorical model (that is, RDMs based on HPP). The degree of cross-cultural concordance in relationship concepts was assessed on the basis of these region-specific representational geometry models.

Consistent with Study 1, we identified the 5D FAVEE space and three HPP categories in both globally aggregated data (Extended Data Fig. 2) and regional data (Supplementary Figs. 4 and 5). Using leave-one-region-out cross-validation, each region's unique representational geometries were accurately predicted by the left-out globally aggregated data (Fig. 3a). The ability of the FAVEE and HPP models to consistently predict relationship representations across regions suggests that they might be universal structures of relationship concepts that can be generalized across the world. In addition, to examine how well the five FAVEE dimensions represent all theoretical relationship features, we performed model comparison analysis between the FAVEE model and other existing theories. We found that the FAVEE model outperformed 15 other theories in data fitting and explained variance across global regions (Extended Data Fig. 3). Therefore, although past theories all attempted to reduce numerous relationship features into fewer components, FAVEE is the most representative, parsimonious and consistent model across cultures.

Although the basic organization of relationship concepts was found to be globally shared, there was also rich cultural variation. For example, people around the world seemed to have a different understanding of public relationships but held similar views on familial and romantic relationships (Extended Data Fig. 4). To further explore these findings, we implemented representational similarity analysis (RSA) to quantitatively model the cross-region variability of representational geometries on the basis of regressions of a variety of ecological, biological and sociocultural variables (Fig. 3b). Religion and modernization were the only two factors that significantly predicted cross-region variability in representational geometries (see the detailed statistics in Extended Data Table 1), and regions with similar religions and modernization levels were found to have similar representational geometries of relationships (Fig. 3c). Here modernization refers to a composite metric based on the education, urbanization and wealth of a country[16], and religion estimates the percentages of adherents of 21 religious denominations (Supplementary Table 3). Follow-up RSAs revealed that the two factors exerted predictive power on distinct dimensions and categories (Supplementary Fig. 7).

To further delineate and elaborate the fine-grained cultural differences, we collected additional data in China ($n = 6{,}128$) (Supplementary Fig. 8) and directly compared it with the USA at a finer scale (Fig. 4). To rule out the effects of language and translation, two rounds of data collection were conducted. In the first round, 159 relationships directly translated from the US relationship list were adopted. In the second round, a new list of 258 relationships was generated by Chinese NLP algorithms (see the details in Supplementary Method 1), which included numerous Chinese-unique relationships (that is, some cannot be translated linguistically, and others are culture-specific; see the full list in Supplementary Table 4). Our analysis revealed no significant differences between the datasets of directly translated relationships and those generated via Chinese NLP algorithms (all $r > 0.622$, all $P < 0.001$; Supplementary Fig. 8), confirming that our results were not influenced by language or translation. There were more intriguing findings in the direct comparisons between the USA and China. We found, when understanding closeness in human relationships, Americans seemed to focus more on physical distance, whereas Chinese focused on psychological distance (Fig. 4c). For example, ancestor–descendant was considered by Americans to be a distant relationship because two sides have infinitely far physical distance. Chinese evaluated this relationship as being less distant due to ancestor veneration in the foundational philosophy of Confucianism (for example, high spiritual intimacy with ancestors). When understanding power in human relationships, individuals in China hold stronger stereotypes of inequality among family members (for example, uncle–nephew; Fig. 4d), which is consistent with the Confucian ideal of filial piety. When evaluating social exchange in private relationships, Americans seemed to experience more concrete resource exchanges than Chinese, which could be associated with their higher modernization level or foundational values linked to capitalism (Fig. 4e). For example, long-distance lovers in the USA often buy gifts such as flowers for each other, whereas symbolic exchanges, such as long telephone calls, were typically observed in Chinese long-distance partners. Together, these subtle cultural differences in relationship conceptualization seemed to be highly interdependent with USA–China differences in religion and modernization level.

Finally, as all 19 global regions were industrial societies, we validated the FAVEE-HPP model in a non-industrial society—the Chinese Mosuo tribe, a small-scale matrilineal society living near Lugu Lake in the Tibetan Himalayas. As a traditional agrarian society, the Mosuo society is distinct from industrialized societies in social organization, economy system, language, beliefs and lifestyle (see key features of the Mosuo society in Extended Data Fig. 5). Field research data from 229 native Mosuo people indicated that Mosuo culture still con-

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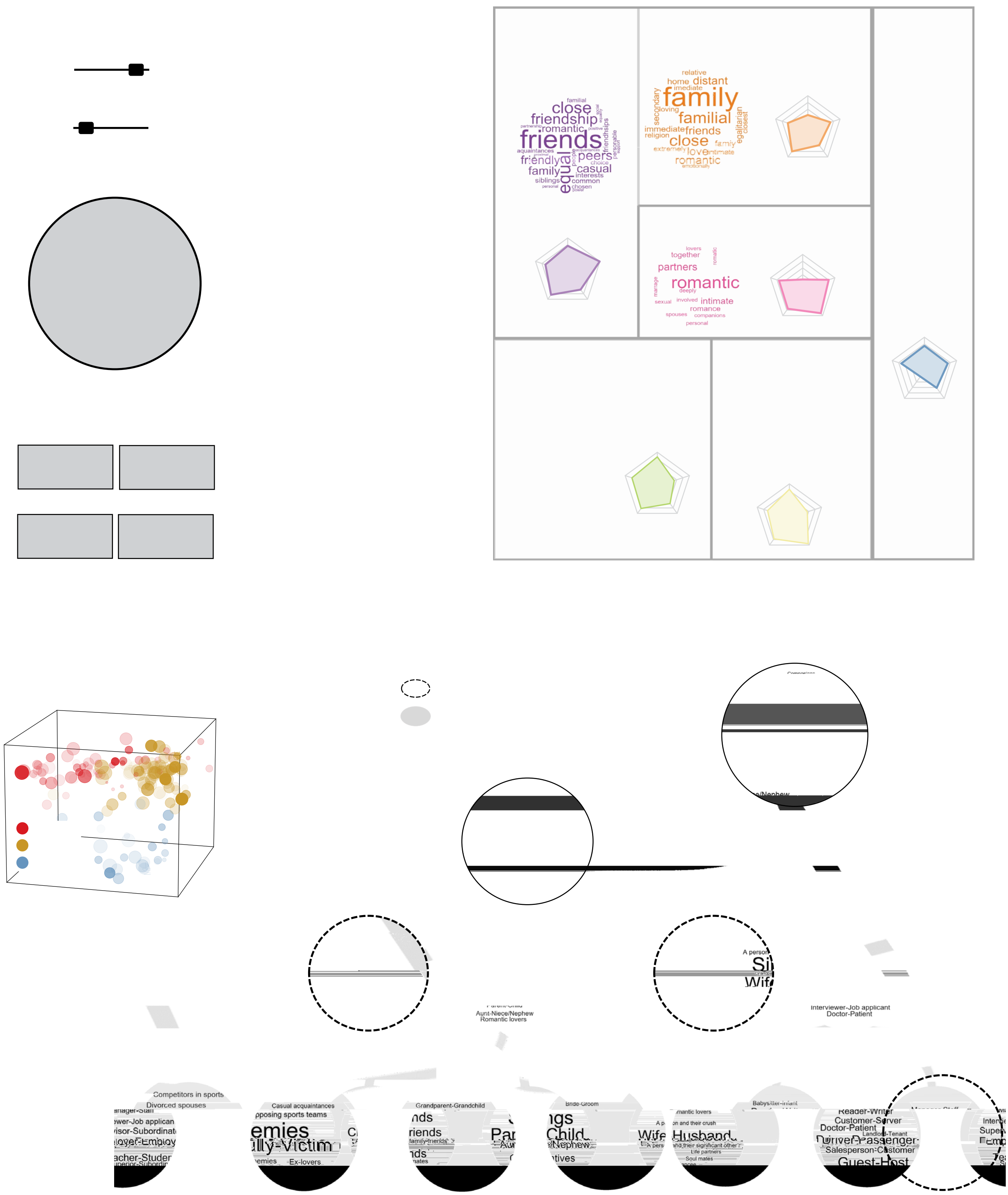
Study 3: relationship representations in ancient cultures

Study 1 investigated how human relationships are mentally represented and discovered the FAVEE-HPP structures. Study 2 examined where in the world the FAVEE-HPP model applies and showed its generalizability to diverse global regions. In Study 3, we explored when in history this model can apply. In Studies 1 and 2, we only examined contemporary societies, which are far from representative of all cultures. An investigation on ancient cultures will help verify the persistence of the FAVEE-HPP model through time.

We employed state-of-the-art NLP techniques to capture ancient people's perception and comprehension of human relationships. This involved analysing large-scale text corpora sourced from historical archives, enabling us to gain insights into their conceptualization of relationships. Analysing texts can offer a unique window into human



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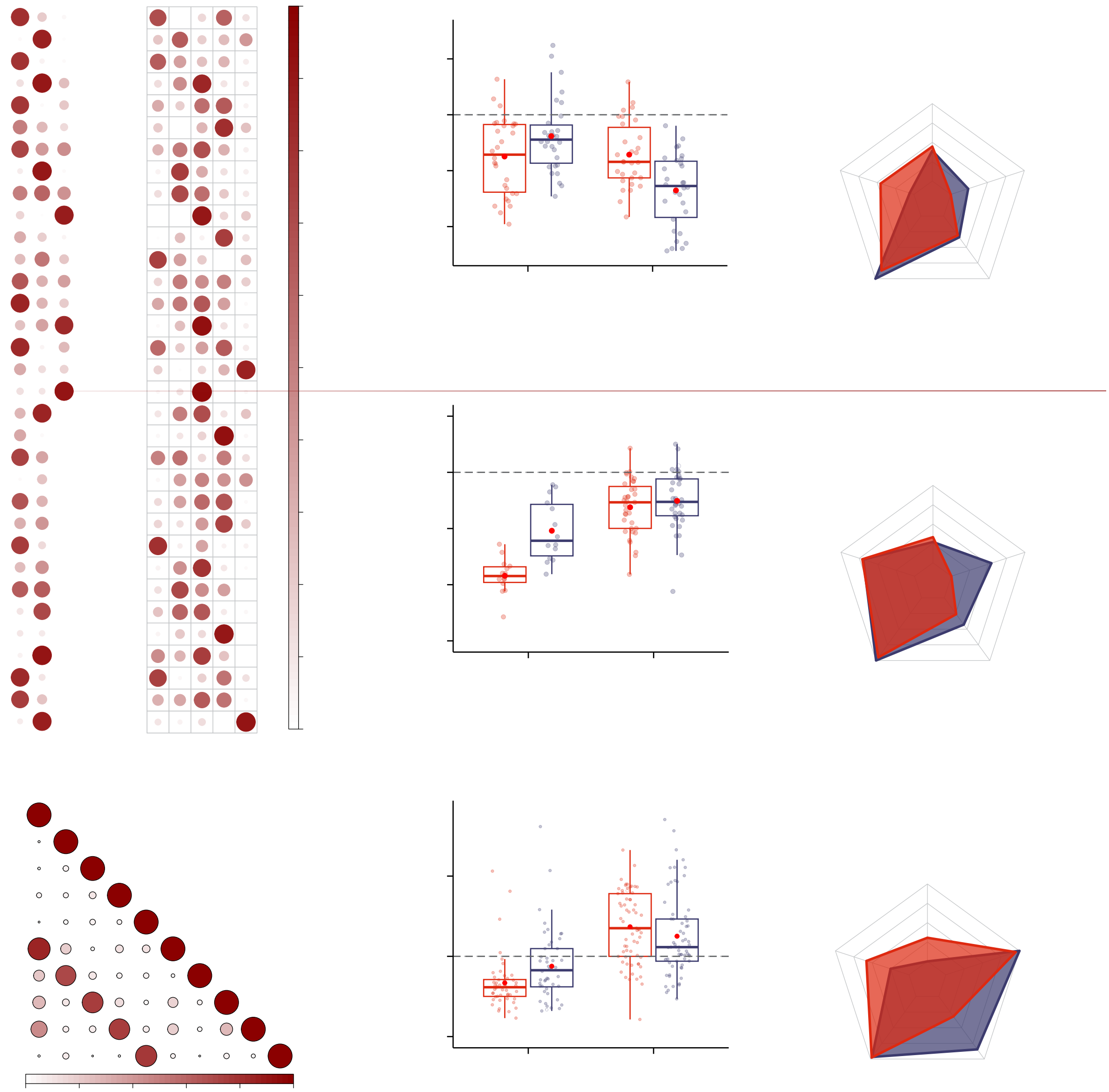

language model used contextualized embeddings of the [MASK] token to predict the most probable words to occur in that position, given the contexts. To enrich the contextual information, we incorporated [DESC], which denotes relationship-specific descriptions generated by a state-of-the-art LLM, GPT-4. These descriptions played a pivotal role in establishing a contextual framework for the subsequent representations of relationships by the language model. After systematic testing with different query types, token positions and embedding layers of the language model (Supplementary Fig. 9), we were able to identify optimal PLM representations highly resembling human relationship representations (r = 0.553, P < 0.001; Fig. 5a). Critically, PCA on PLM representations generated components (Fig. 5b) corresponding well with the FAVEE structures (all r > 0.470, all P < 0.001; Fig. 5c in purple).

accurate historical context, we first prompted GPT-4 to describe the relationships within the context of ancient China. We then recruited human experts in ancient Chinese language, literature and history to manually refine the descriptions and express them in Classical Chinese. This ensures that the DESC effectively matches the linguistic features and relationship characteristics of the ancient era (Supplementary Method 2). These experts also carefully selected 120 relationships that existed in ancient China (Supplementary Table 6). As expected, FAVEE structures can be identified after applying PCA on ancient PLM embeddings (all $r > 0.287$, all $P < 0.001$; Fig. 5c in green). Next, if the FAVEE-HPP model can capture relationship representations in history, then the relationships that are closer to each other within FAVEE-HPP space should be represented by vectors that are closer to each other in ancient PLM embeddings. Indeed, for both FAVEE dimensions and HPP categories, we found significant correlations between RDMs in human ratings and RDMs in ancient PLM embeddings (Fig. 5d). Model comparison analysis suggested that the FAVEE model outperformed other theoretical models in predicting ancient and modern PLM embeddings (Fig. 5e). To further reveal the difference between ancient and modern China, we evaluated the relative contribution of each FAVEE dimension when predicting relationship representations in ancient and modern PLMs (Fig. 5f). We found that 'formality' explained more variance in modern than in ancient times (modern, 0.279; ancient, 0.178), whereas 'equality' accounted for more variance in ancient than in modern times (modern, 0.148; ancient, 0.243). This suggests that, compared with modern Chinese, ancient Chinese might put more weight on equality features (for example, social hierarchy) but less on formality features (for example, occupations) when understanding relationships.

We also performed expert validation on the ancient PLM to check whether it had expert-like knowledge on ancient relationships. A group of university scholars ($n = 44$) were asked to rate all 120 relationships in the context of ancient Chinese culture, and FAVEE-HPP structures can be reliably identified from their ratings (Supplementary Fig. 10). Critically, ancient PLM embeddings showed higher agreement with observation and direct experiences with others and understand new dimensions such as activeness (old versus new friends), equality (for example, teachers–peers) and exchange (for example, seller–buyer). In adulthood, acculturation to a new society involves learning the host culture's social norms and rules when interacting with local people. In addition, the present work investigated relationship conceptualization at only the cultural and population levels. It is apparent that cognition about relationships is subjective, varied and dynamic at the individual level, and how people think about relationships might vary depending on salient features in the contexts. The FAVEE dimensions and HPP categories could function as cognitive maps to help individuals navigate social environments (such as a 'relationship compass') and set standards to determine the satisfaction and stability of a relationship[28,29]. For example, individuals who grew up in a family with challenges and had chronic peer rejection might form negative impressions about familial and affiliative relationships (for example, with negative scores in valence and activeness). Likewise, individuals who had harmonious experiences with employers, clients or co-workers might adopt more positive views on public relationships (for example, with positive scores in valence and equality). The FAVEE-HPP framework establishes relatively objective and quantitative measures of relationships that can be compared across contexts, individuals and groups. Future research could use the framework to develop psychometric tests to measure where an individual lies on the spectrum of each of the five dimensions (like the Big Five personality test) and quantitatively examine how individual differences in relationship representations are linked to interpersonal difficulties in daily life[30] and whether relationship representations are abnormal in clinical populations (for example, those with autism or sociopathy).

The present work features replication and generalization. We attempted to extend and improve on prior work by being more comprehensive in several aspects, including preregistering our studies, using high-powered samples, including diverse types of relationships, analysing data with different tools and algorithms, and replicating representational models across different cultures (contemporary industrial societies, ancient societies and matrilineal tribes) and interpersonal contexts (dyadic, triadic and group relations). We also quantified the robustness of all results and showed that a subset of 40 relationships was good enough to replicate all findings based on 159 relationships (Supplementary Fig. 11).

However, our work also has several limitations. First, the mental representations of relationships are an organized body of information that reflects values, rules, concepts, scripts, affects, motives, expectations and memories associated with a relationship. The present work only taps the lay theory (that is, vernacular beliefs), which may differ from the actual organization of relationships in human society[31]. Future work needs to examine the social acts and interactions across relationships. Second, FAVEE-HPP as the universal structure of relationships is far from conclusive. The present work primarily used online populations and data-driven approaches, which was a double-edged sword. More data and investigations are needed to explore factors or boundary conditions that could influence the stability, validity, representativeness and generalizability of the FAVEE-HPP model. For simplicity and convenience, we chose the acronym FAVEE as the name for our model, but the global data showed that formality is not always the most important dimension. The different ordering of dimensions in different regions requires further investigation as it could reveal interesting cultural differences. Third, the FAVEE-HPP model was decomposed from many theoretical features originating from layperson languages. A more scientifically rigorous approach is needed to create a valid and reliable taxonomy of human relationships. Fourth, due to limited resources of ancient culture experts and high-quality PLMs, Study 3 examined relationship representations only in ancient China. Future research is encouraged to validate the FAVEE-HPP model in other historical contexts (for example, in Hebrew, Greek, Tamil and Old English).

Methods

Participants

All studies in this report were approved by the Institutional Review Board of Beijing Normal University (IRB_A_0024_2021002), and informed consent was obtained from all participants. Study 1 recruited 1,065 online US participants via MTurk and 60 offline US participants. Study 2 was preregistered (https://osf.io/swr2c) and recruited 17,686 online participants across 19 global regions via MTurk, CloudResearch, Credamo and the NaoDao platform[32,33]. In addition, 229 native Mosuo people were recruited from Yongning Township (Yunnan Province, China), using a field research data collection style (that is, through face-to-face interviews and door-to-door paper surveys). Study 3 recruited 44 scholars specialized in ancient Chinese culture for expert evaluation of the NLP method. Moreover, to test the FAVEE-HPP model in non-dyadic relationships, we recruited 380 online US participants (via MTurk) and 242 online Chinese participants (via the NaoDao platform). Participants across all studies were native speakers who grew up or lived for the longest period of their life in the targeted regions, with diverse demographics (Supplementary Fig. 13). The survey was translated into the local written language, and detailed guidelines for translation can be found at the Open Science Framework website. All participants received monetary compensation after completing the tasks.

Power analysis was performed to predetermine the sample size. To establish a design with adequate statistical power, we conducted a pilot study ($n = 721$, recruited from MTurk) using the dimensional survey from Wish et al.[10]. We collected at least 80 participant responses for each relationship on each evaluative feature, and the results of Wish et al.[10] were completely replicated (Supplementary Fig. 12). We ran a Monte Carlo simulation test to derive the minimally required responses in each condition to maintain a stable and consistent PCA result. PCA was performed on each subsample (from 2 to 40, with 1,000 iterations for each subsample), and loading scores and relationship scores were compared with the overall dataset using Pearson's correlation. The simulation results (Supplementary Fig. 12c) indicated that subsamples with ten responses were almost identical to the entire dataset (rating correlation $r > 0.95$) and thus should be adequate to ensure highly similar derived PCA components (loading score correlation $r > 0.90$; relationship score correlation $r > 0.95$).

Sampling of human relationships

A data-driven approach based on NLP was used to generate a comprehensive list of human relationships (see Supplementary Method 1 for the details). Seed words were created via brainstorming and social media searches by a set of participants ($n = 15$ for the USA and $n = 27$ for China). Text embedding was used to find high-co-occurrence words relating to seed words by calculating the cosine distance between word vectors. The list of words was filtered to leave only nouns. Next, the list was filtered for frequency and was manually checked to keep only words related to human relationships. Finally, we paired the words on the basis of the meaning of relationships and added relationships that were pulled from the literature, resulting in the final relationships word list (159 for the USA and 258 for China). See further methodological details in Supplementary Figs. 1 and 8 and the full list of 159 English relationships and 258 Chinese relationships in Supplementary Tables 2 and 4.

Evaluative features

A comprehensive literature search was performed to find all relevant theories and models that were proposed to explore the basic forms of human relationships. Thirty conceptual features were summarized and extracted from 15 prominent theories in Study 1. Redundant features were combined across theories (see Extended Data Fig. 1 and Supplementary Table 1 for the details). Note that many of these theoretical features were originally derived from dimensionality reduction

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or clustering techniques, but here they were prepared to be further reduced into higher-order components. Study 2 added three extra theoretical features (morality, trust and generation gap) from the cross-cultural literature[34–36], so a total of 33 features were evaluated.

Dimensional survey

The participants completed an online survey where they rated human relationships on bipolar Likert scales. At the top of each page, the participants were cued to rate relationships on a given evaluative feature (for example, activeness), along with two phrases on opposite ends of a presented slider bar (for example, passive versus active). These two phrases represented the opposite ends of the bipolar features. Participants moved the slider towards the phrase that they felt best related to the presented relationships. Since certain features were quite obscure (for example, communality and reciprocity), we presented each feature with a detailed definition plus an exemplary relationship in the survey (Supplementary Table 1). Once the participants confirmed their understanding of each feature, they moved to the rating part. The participants were asked to consider all aspects of the relationships, including the way the individuals in each relationship typically think and feel about each other, how they act and react towards each other, how they talk and listen to each other, and any other characteristics of the relationships that occurred to them. The participants were instructed to focus not on their personal experiences with a specific relationship but rather on their general knowledge (that is, common sense or stereotypical understanding) about such relationships. Attention-check questions were used to ensure that the online participants were actively engaged in the survey and not answering questions in specific patterns or answering randomly. To avoid potential fatigue and inattentiveness, a between-subject design was used for all online participants to keep the survey short and effective (~20 min). Each participant was randomly assigned to a subset of relationships (for example, five to eight relationships) and had to rate them on a subset of evaluative features (for example, 10–11 features). To replicate the results from the between-subject design, a within-subject design was adopted for offline participants in Study 1, where each participant was asked to rate all relationships on all features in the laboratory (which took them three hours to complete). To rule out the effects of cross-cultural variations in online data quality and general semantic knowledge, the participants were asked additional questions on the size and colour of common objects (for example, animals, fruits, vehicles, tools and 88.1hmy5(().5(f).hc osenee).Ws

Language models and embeddings

We used PLMs and LLMs to probe ancient people's perception and comprehension of human relationships. For the modern Chinese PLM, we employed the word-based Chinese-RoBERTa-Base model from UER-py Modelzoo[38]. We selected this model due to its focus on the mask language modelling task during the pretraining phase. Moreover, it takes into account the characteristics of the Chinese language by using words rather than characters as units, and it has been trained on a large-scale, publicly available corpus of modern Chinese text. For the ancient Chinese PLM, we used BERT-ancient-Chinese[22], which was trained on a large-scale ancient Chinese corpus including historical texts from 1046 BCE to 1912 CE.

We adopted an approach to generate human-like PLM embeddings (Fig. 5a), which was previously proposed by Cutler and Condon[19] to identify Big Five personality structures in language models. We compared different queries and layers of embeddings (Supplementary Fig. 9). The [DESC] component in the query was generated by GPT-4 in October 2023 with the temperature parameter set to zero to ensure reproducibility (see exemplar prompts in Supplementary Method 2). Details of the labels and descriptions for ancient and modern Chinese relationships can be accessed via the Open Science Framework website.

RSA and model comparison

To uncover which cultural variables account for the cross-cultural variance in relationship representations, we performed RSA multiple regression[39] (Fig. 3b). For each global region, cultural variables of language, personality, socio-ecology (that is, subsistence style, historical disease prevalence and climates), modernization, genetics, religion, politics and the Hofstede 6D culture model were collected from multiple open databases, such as the World Values Survey, Timeanddate and Worldbank (see Supplementary Table 3 for the details). For each cultural variable (for example, modernization), an RDM was computed where each cell represents the dissimilarity of two regions on this variable (for example, the dissimilarity of China and Portugal according to their modernization level). For each representational geometry (that is, full-feature, dimensional or categorical), we also created an RDM to represent the dissimilarity of relationship representations across regions. We then performed a linear regression model in which cultural variable RDMs were predictors, and relationship representational geometry RDM was the outcome variable. The noise ceiling was estimated using the mean relationship RDMs of $n - 1$ regions to predict the relationship RDM of the remaining region, which reflected the inherent heterogeneity of the relationship RDMs. The Mantel test was used to assess the statistical significance of each RSA[40,41]. We permuted the order of RDMs of cultural variables while holding the representational geometries constant, recalculated the regression and repeated the process 10,000 times. This test allowed us to compute a P value for the representational geometries based on the F statistic of the multiple regression. We performed a one-sided test since a negative value is not meaningful and only positive similarities are expected[20,42].

Study 3 implemented RSA correlations between language models and the human-rating FAVEE-HPP model. Specifically, we transformed PLM embeddings (258 × 768 or 120 × 768 matrix) into a cosine similarity matrix (258 × 258 or 120 × 120). This matrix was then correlated with the lower triangle of the RDMs derived from the FAVEE dimensions (which represents the distances between pairs of relationships in 5D FAVEE space) or RDMs from the HPP categories using Spearman correlation. The noise ceiling was estimated by correlating human-rating RDMs derived from the FAVEE-HPP model with human-rating RDMs from 33 dimensional features (Fig. 5d).

Robustness test

The robustness test across different numbers of relationships was quantified using the same method as Lin et al.[43]. We removed human relationships one by one and reperformed all analyses (for example, PCA, clustering and cross-cultural RSA). The sequence to remove relationships was implemented as follows: all pairs of relationships were ranked from the most to the least similarity in the multi-arrangement task, and the relationship with the lower familiarity rating was removed first from each pair. Pearson correlations were calculated between metrics from the full set and from the subsets to determine the robustness of the results (see Supplementary Fig. 11 for the details).

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

All data used in this project are accessible via GitHub (https://github.com/BNU-Wang-MSN-Lab/FAVEE-HPP) and deposited in the Open Science Framework (https://osf.io/nfkmj) and can be interactively viewed and freely downloaded at a dedicated website (https://bnu-wang-msn-lab.github.io/FAVEE-HPP). A supplementary video is also provided to elaborate the FAVEE-HPP framework (https://insula.oss-cn-chengdu.aliyuncs.com/favee/FAVEE-HPP.mp4).

Code availability

All data analysis code is available via GitHub (https://github.com/BNU-Wang-MSN-Lab/FAVEE-HPP).

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Extended Data Fig. 1 | Existing theories in relationship science. 30 conceptual features were summarized from 15 prominent theories. Redundant features were combined across theories (see central column for final 30 features). It seems that valence and equality were the most frequently mentioned features. Note that many of these theoretical features were originally derived from dimensionality reduction or clustering techniques, but here, they were prepared to be further reduced into higher-order components. Three extra theoretical features from cross-cultural literature (that is, morality, trust, generation gap) were added for Study 2, which were not listed here. Please see more detailed information about each feature in Supplementary Table 1.

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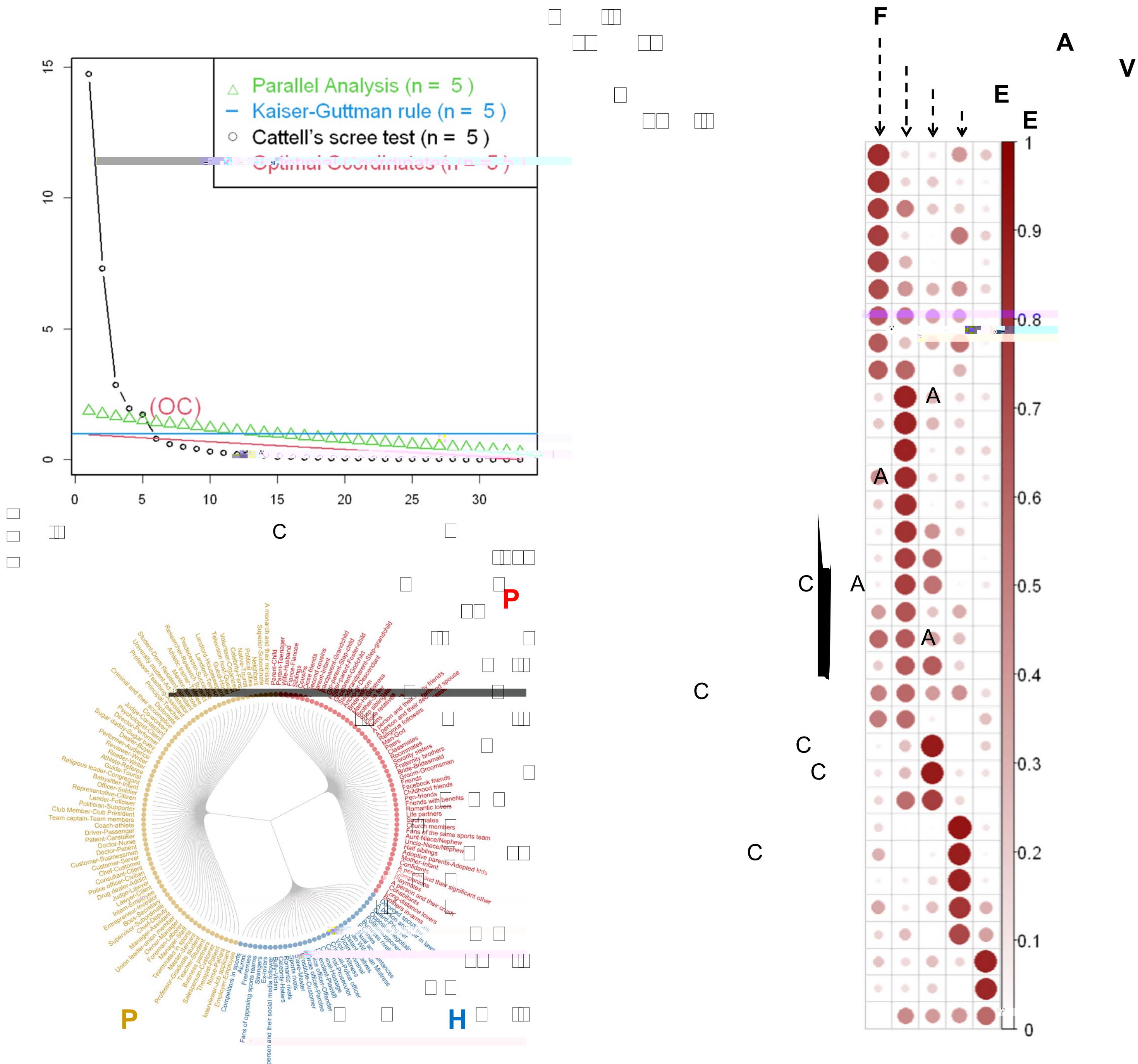

Extended Data Fig. 2 | The dimensional and categorical models derived from global data (n = 17,686). **a**, Four data-driven metrics consistently indicated that the optimal number for PCA was five. **b**, PCA loadings for five principal dimensions. **c**, K-means clustering solution identified three categories labelled as Hostile, Private, and Public, with the highest silhouette score of 0.295 at k = 3. These results suggested that the FAVEE-HPP model proposed in Study 1 can be well replicated by large-scale global data. In addition, for each global region, the same five dimensions and three clusters can also be identified (see Supplementary Fig. 4 and Supplementary Fig. 5).

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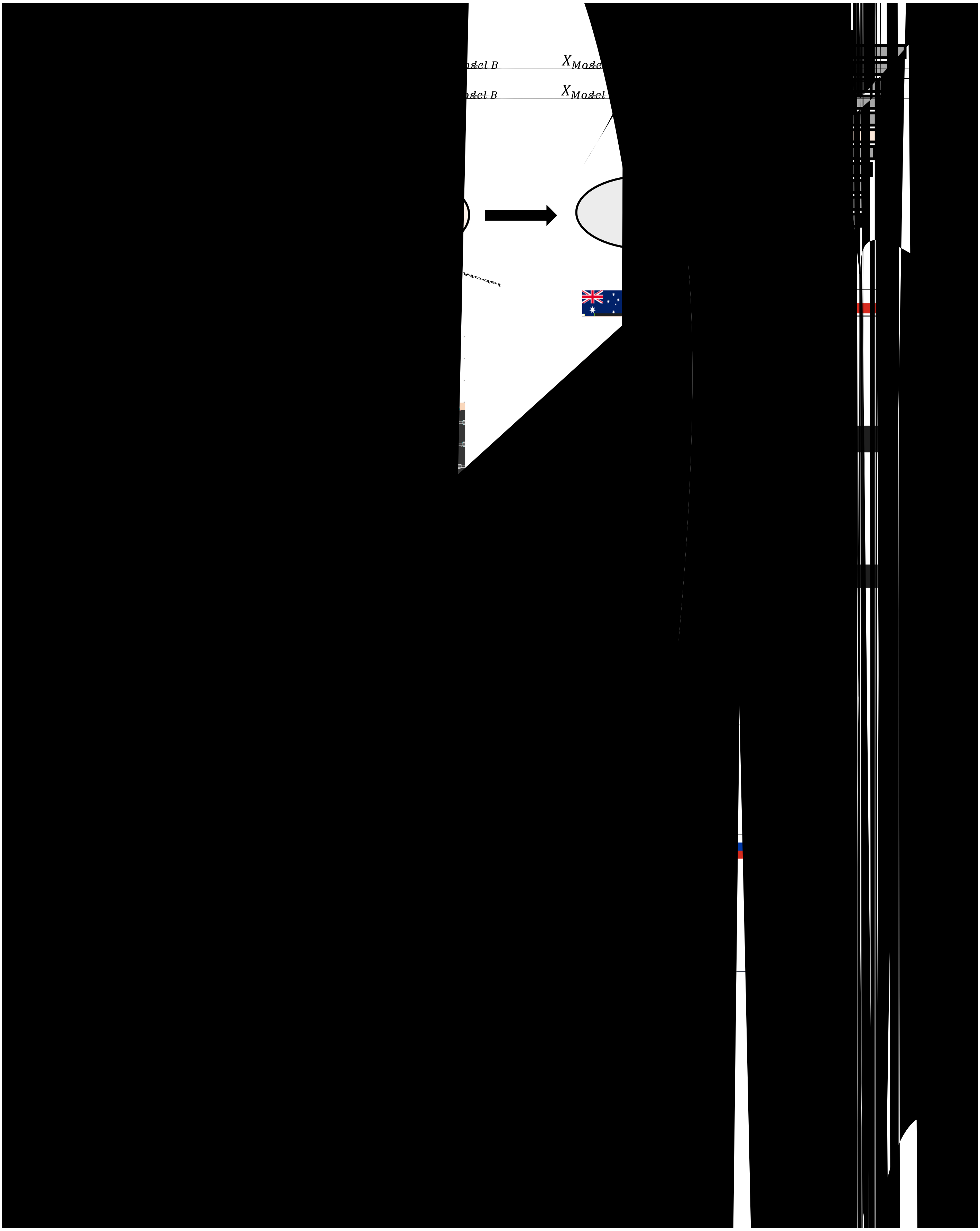

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Extended Data Fig. 3 | Model comparison in performance consistency across the globe. a, To examine how well a model can represent all theoretical relationship features, we used linear combinations of features in each model as regressors to predict each of remaining theoretical features (that were not included in that model) and calculated adjusted R^2 for each region. **b** and **c**, Across global regions, FAVEE model (mean adjusted $R^2 = 0.489$, mean BIC = 364.794) outperformed other 15 existing theories in both explained variance and data fitting, with 100,000 bootstrap resamples used to estimate the mean differences (99.9% confidence interval). Error bar (standard error) represents performance variance across 19 regions. **d**, Top five models in each global region (FAVEE was the best in 17 out of 19). Note: A more stringent way of model comparison was attempted where the number of predicted features was controlled between two models, and similar results were found (see Supplementary Fig. 6). $^{*}P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$.

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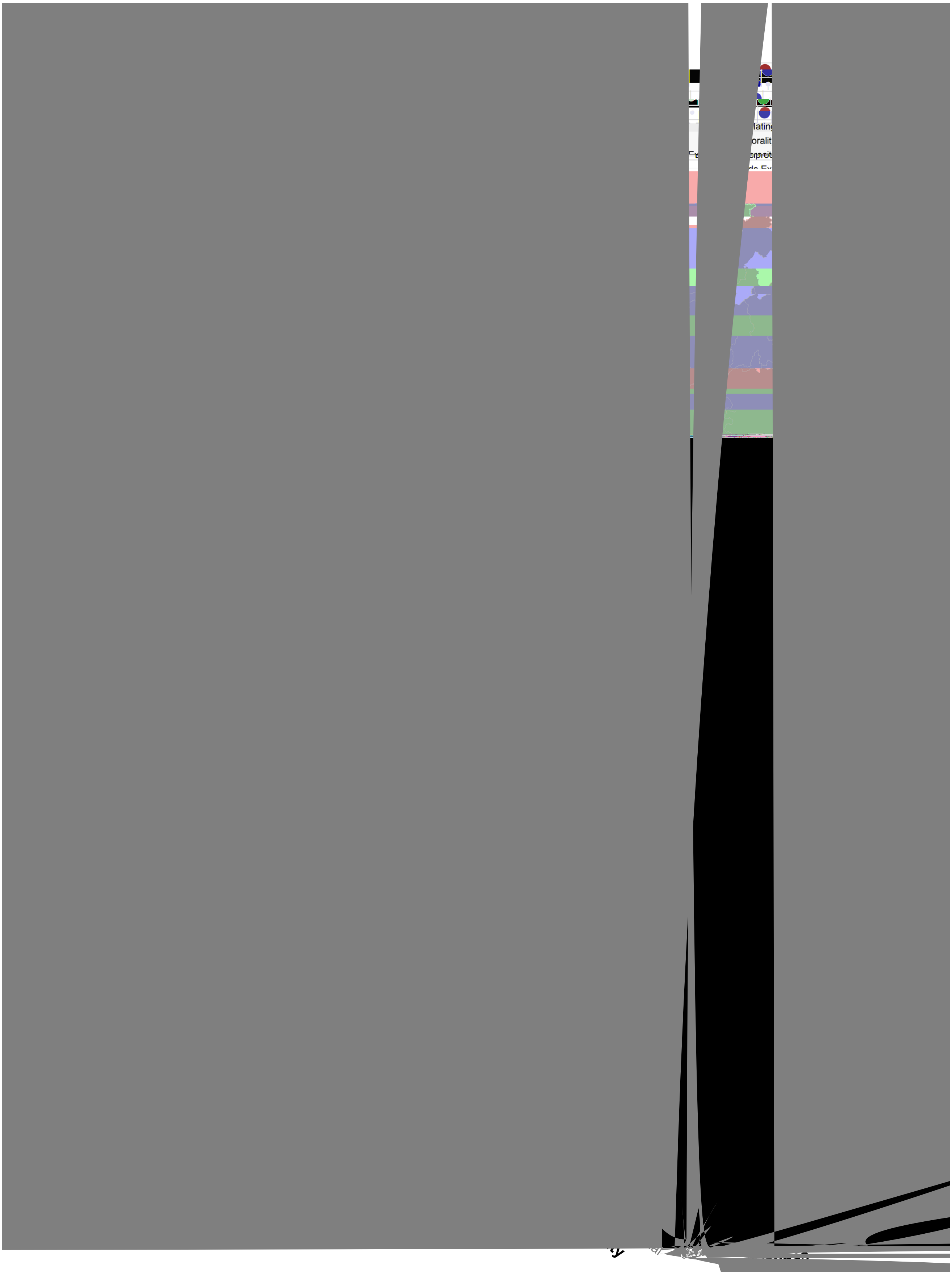

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Extended Data Fig. 5 | Model validation in a non-industrial society. a, key features of the Mosuo society and its geographical location (dash line box). **b**, PCA showed identical FAVEE dimensions for Mosuo Chinese, Han Chinese, and world-averaged data. Through field work, we identified 75 typical relationships in Mosuo culture (see Supplementary Table 5). **c**, The optimal number of PCA components for Mosuo was five. **d**, Spearman's correlation of loading scores across three datasets. Their derived FAVEE dimensions were well corresponded. **e**, K-means clustering on Mosuo relationships identified the HPP model. **f**, A similar dimension-category hybrid model was observed in the Mosuo society, which replicated the findings in Study 1 (see Fig. 2c).

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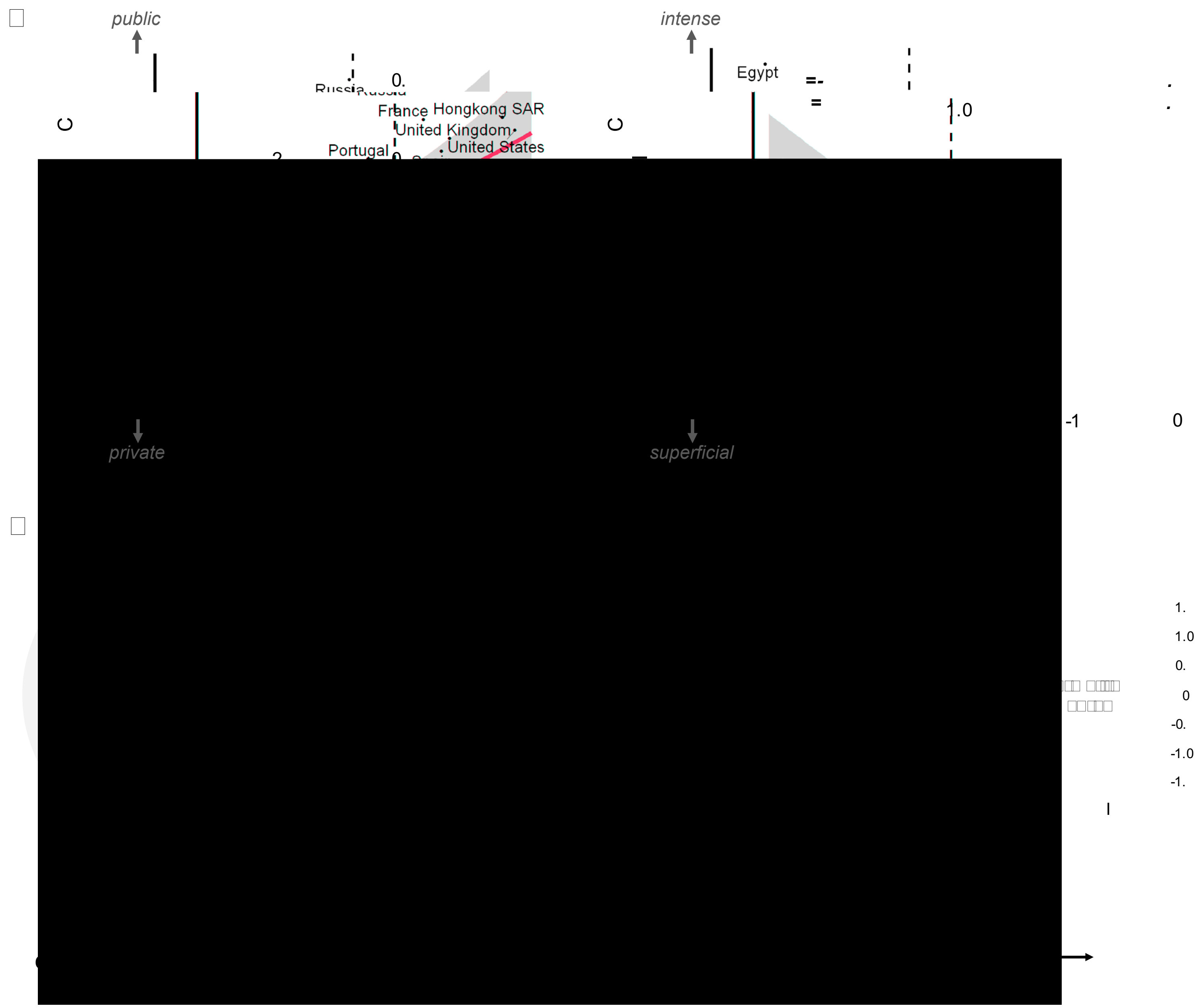

Extended Data Fig. 6 | Conceptual differences in the word '*neighbours*' across the globe. a, For each region, people's understanding (conceptual beliefs) of '*neighbours*' was estimated by interrogating its surrounding relationships in the semantic neighbourhood of representational space. Fifteen nearest relationship words were selected based on the smallest Euclidean distance with '*neighbours*' on all evaluative features. We found that a country's modernization level was positively correlated with the formality score of '*neighbours*' surrounding relationships but negatively correlated with the activity intensity score (Spearman correlation, two-tailed). This suggests that as a country's modernization level increases, '*neighbours*' become a more public, impersonal, and superficial relationship. The shaded area represents the 95% confidence interval. **b**, Taking China (middle level of modernization), Israel (high level modernization) and the US (highest level of modernization) as examples. All 159 relationships were plotted in the 2D t-SNE space, with the nearby 15 relationships zoomed in for better visualization. For China, only informal relationships (in red colour) surround the Chinese word '*neighbour*' (' '), indicating that '*neighbours*' are considered private and personal relationships. However, for Israel and the US, an increasing number of public relationships (in blue colour) appear nearby, indicating that '*neighbours*' are conceptualized as being more formal and impersonal. Together, these results demonstrate that although translation dictionaries provide equivalent words of relationships in different languages, their conceptual meanings are not always the same. Their variations (at least for the concept '*neighbours*') were dependent on the country's level of modernization (for example, '*neighbours*' in large cities are often unknown to each other due to greater mobility led by urbanization). On the other side, these results illustrate how cultural factors such as modernization can deform the local representational geometries of relationship concepts.

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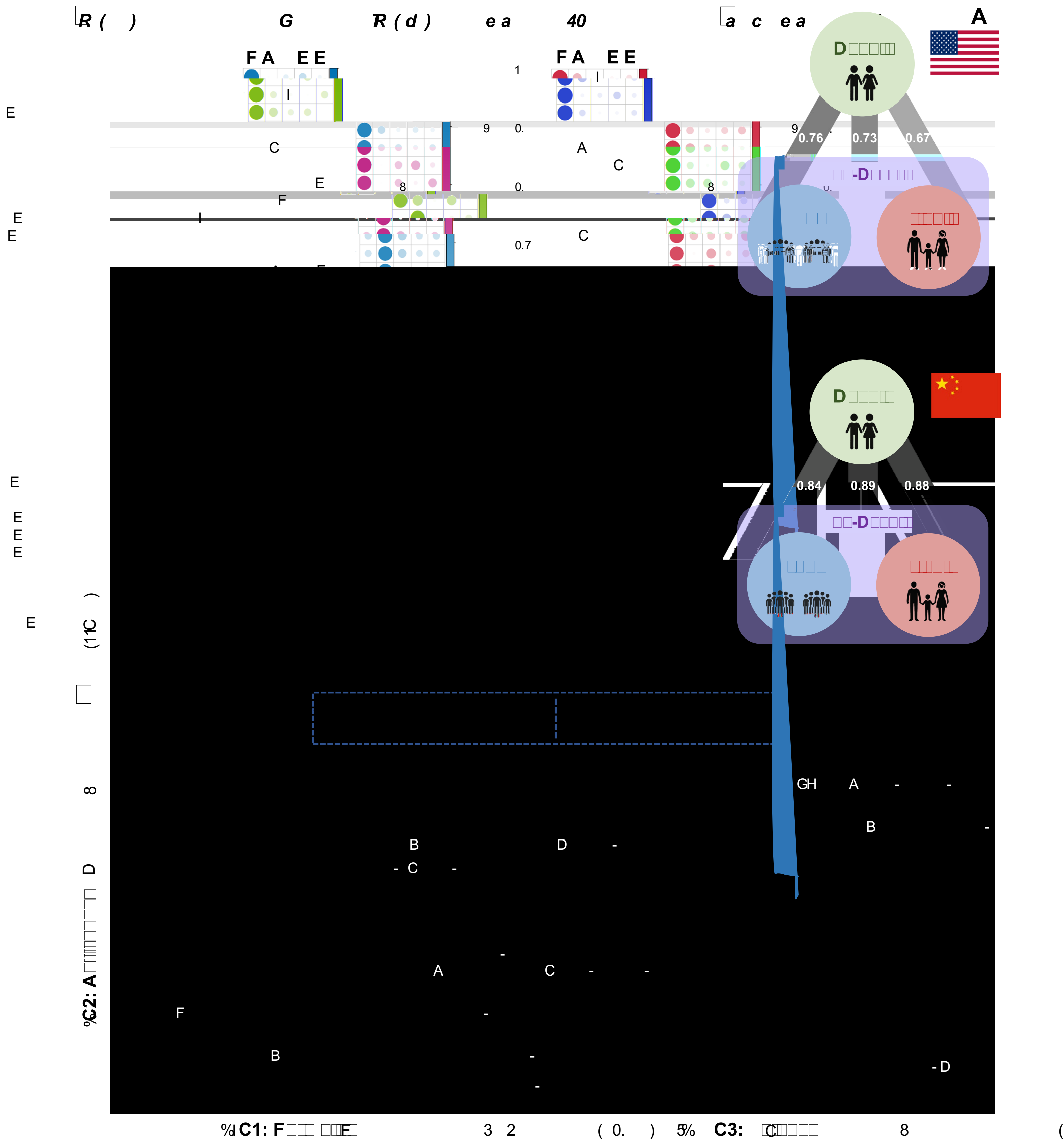

Extended Data Fig. 7 | See next page for caption.

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Extended Data Fig. 7 | Good generalizability of the FAVEE model to non-dyadic relations in the US and China. **a**, PCA loadings on 33 theoretical features for group relations and triadic relations in the US (n = 380). See Supplementary Table 7 for the full list of 40 group relations and 34 triadic relations. **b**, In general, there were high correlations of FAVEE structures between dyadic and non-dyadic relations in the US (r = 0.73). Within non-dyadic relations, dyadic relations also showed high correlations with group relations (r = 0.76) and triadic relations (r = 0.67). **c**, Similar results were observed in China (n = 242), with high correlations of FAVEE structures between dyadic and non-dyadic relations (r = 0.89). **d**, For illustration purpose, all group relations (blue) and triadic relations (red) in the US data were plotted in the 5D space based on their scores on each FAVEE dimension.

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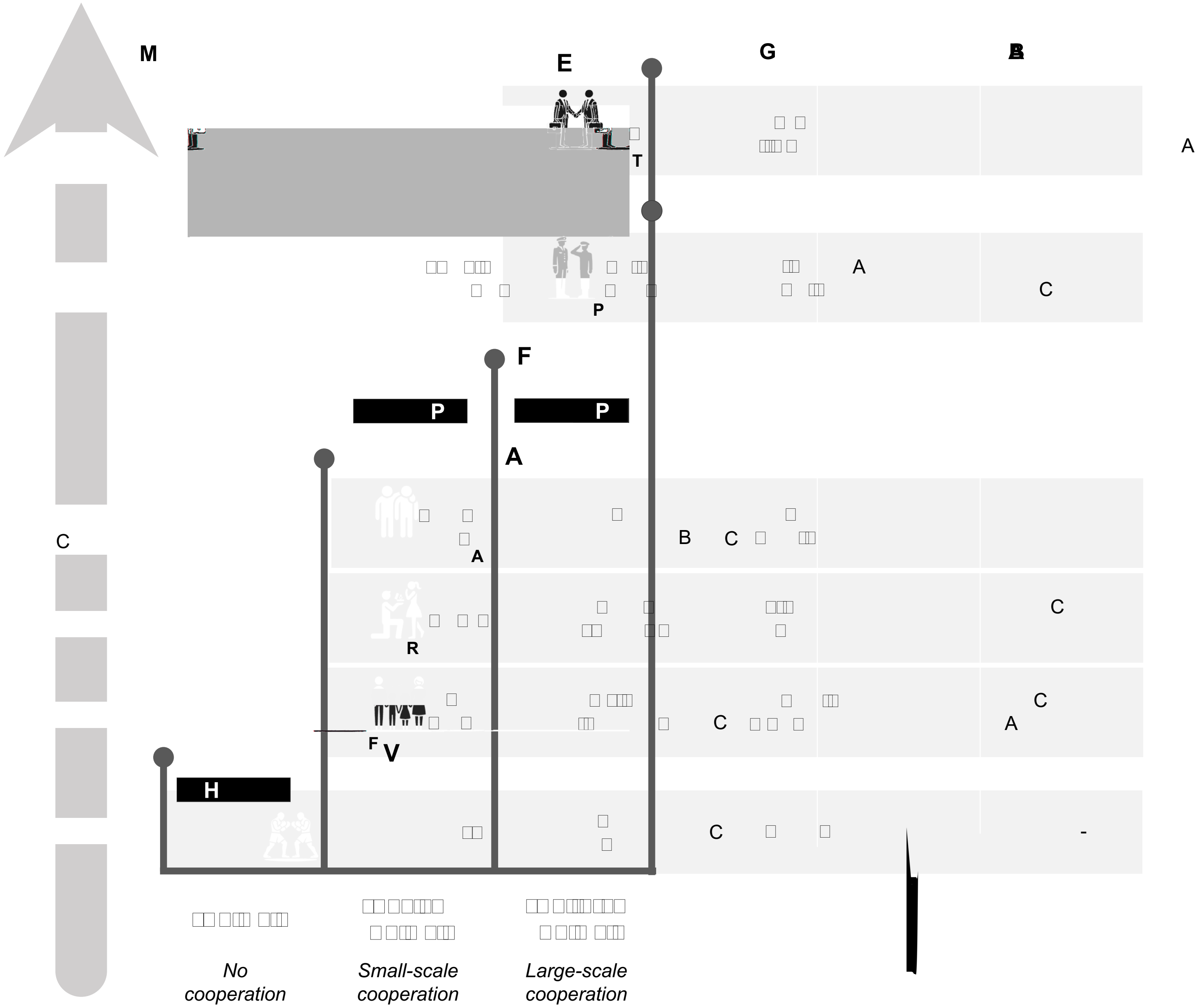

Extended Data Fig. 8 | Functionality of FAVEE dimensions and HPP categories. The human mind involves implicit cognitive models for forming and maintaining relationships ('relational schemas'), such as a shared understanding of the rules and norms governing interactions and the coordination of mental processes for social navigation and adaptation. The FAVEE-HPP framework posits that relationship concepts are primarily organized in a five-dimensional space with three default categories. These five dimensions might reflect different levels of motivations (for example, Maslow's hierarchy of needs, see left arrows), for example, valence for resource competition, activeness for emotional support and belongingness, formality for social order, equality for power, and exchange for fairness. Three categories might be configured for three levels of cooperation, which echoes Roy Baumeister's theory on how humans evolved from 'animals' (no cooperation, keeping hostile towards others), 'social animals' (small-scale cooperation based on private relationships) and to 'cultural animals' (large-scale cooperation based on public relationships)[23]. The three default HPP categories can be further classified into six canonical types of relationships, which are assumed to be associated with distinct goals, affects and behaviours. Circles and squares represent dimensions and categories, respectively. Please note that, although animals may have certain dimensions and categories, they are different from those of humans. For example, power in animals is typically defined by biological and behavioural characteristics (for example, body size, strength, vocalization), while high power in humans is often based on abstract symbols and cultural conventions (for example, reverence for elders and the divine[1]). Likewise, money creates a system of trust that enables exchange and cooperation between strangers in human society[44].

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Extended Data Table 1 | Multiple Regressions on Full-feature, Dimensional, and Categorical Models in Representational Similarity Analysis in Study 2 (significant results are in bold)

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	D	.	. 4	.61 4	. 0-00 2	. 0 99	0 0 2	0 0 5 9	0 0	0		555
	. 6	.16	. -G	.	. 0 0	. 0 8 4 5	0 5 2 1	0 7 0 6 5 4	0 0	0 7 5		5
1	.		-G2	3	0							