Behavioral/Cognitive

Neural Synchrony and Consumer Behavior: Predicting Friends' Behavior in Real-World Social Networks

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The endogenous aspect of social influence, reflected in the spontaneous alignment of behaviors within close social relationships, plays a crucial role in understanding human social behavior. In two studies involving 222 human subjects (Study 1: $n = 175$, 106 females; Study 2: $n = 47$, 33 females), we used a longitudinal behavioral study and a naturalistic stimuli neuroimaging study to investigate the endogenous consumer behavior similarities and their neural basis in real-world social networks. The findings reveal that friends, compared with nonfriends, exhibit higher similarity in product evaluation, which undergoes dynamic changes as the structure of social networks changes. Both neuroimaging and meta-analytic decoding results indicate that friends exhibit heightened neural synchrony, which is linked to cognitive functions such as object perception, attention, memory, social judgment, and reward processing. Stacking machine learning-based predictive models demonstrate that the functional connectivity maps of brain activity can predict the purchase intention of their friends or their own rather than strangers. Based on the significant neural similarity which exists among individuals in close relationships within authentic social networks, the current study reveals the predictive capacity of neural activity in predicting the behavior of friends.

Key words: **endogenous similarity; machine learning prediction; neural similarity; products evaluation**

Significance Statement

The current study reveals that close social relationships exhibit dynamic behavioral and neural synchrony, with brain activity better predicting purchase intentions of individuals and their friends. The findings illuminate the neural basis of endogenous consumer behavior and offer new insights into how social networks shape decision-making within real-world networks.

Introduction

Social relationships represent a fundamental component of human behavior, exerting significant influences on decision-making, emotional responses, and cognitive processes across a variety of contexts. The concept of social impact refers to the changes in an individual's cognition, emotions, or behaviors resulting from interactions with others (Latané, 1981). This phenomenon is pervasive, shaping outcomes in areas ranging from education to economics, and has been extensively leveraged in fields such as marketing, where strategies driven by social influence are increasingly prominent (Wang et al., 2023; Zhao et al., 2023). Despite its ubiquity, the challenge of understanding the underlying mechanisms of social impact remains significant.

Social impact theory suggests that the influence exerted by social relationships can be categorized into exogenous and endogenous impacts (Manski, 1993). Exogenous impact is defined as the influence of exogenous peers, which is the tendency for individual characteristics and behaviors to spread and change through social relationships (Bhukya and Paul, 2023). Endogenous impact, on the other hand, is defined as the tendency for individuals to exhibit similar behaviors spontaneously. It may emerge either from preexisting trait matching during friendship formation (McPherson et al., 2001; Currarini et al., 2010) or from behavioral convergence driven by average peer influence and social diffusion (Centola, 2010; Lewis et al., 2012). Although previous studies mainly focused on the exogenous aspect of social impact, the importance of endogenous impact has been increasingly recognized. For example, Akar and Topçu highlighted that the neglection of endogenous homophily factors could lead to a significant overestimation of the

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effects of consumer attitudes toward social media marketing (Akar and Topçu, 2011). Bhatt found that customers with social connections exhibited similar purchasing behaviors (Bhatt et al., 2010). Additionally, Parkinson provided evidence that neural responses in regions such as the parietal lobe, basal ganglia, and amygdala were notably more similar among friends when viewing audiovisual stimuli than nonfriends (Parkinson et al., 2018). Other studies, such as that by Hyon, indicated that resting-state functional connectivity could predict friendship within social networks (Hyon et al., 2020). Nevertheless, there remain unresolved questions on the direct relationship between specific behavioral similarities and corresponding neural similarity and whether brain activity can reliably predict the behavior of other social connections.

The current study investigates endogenous similarity manifestation within consumer behavior. The objective of this study is to uncover the neural mechanisms which drive this phenomenon, as well as predict purchase intentions of their own and their friends' by examining neural activity patterns in real-world social networks. This emphasis on consumer behavior is motivated by two fundamental factors. First, social interaction-driven business models, such as branded social networks (Barreda et al., 2015), live-streaming commerce (Qu et al., 2023), and group purchasing (Jing and Xie, 2011), highlight the crucial role of human sociality in consumer behavior. Second, the pervasiveness of consumer behavior, such as everyone's daily participation in consumption activities, underscores its broad relevance. The burgeoning status of consumer neuroscience has reflected the increase of academic interest in this area (He et al., 2021; Pozharliev et al., 2022; Bhardwaj et al., 2023).

The investigation of how social distance in real-world social networks influences consumer behaviors, such as product liking and purchasing intention, was first carried out (Study 1A). Then the dynamic changes in behavioral similarity were examined, and the same social network was retested 1 year later accompanied by the evolution of friendships (Study 1B). Finally, these behavioral findings were replicated and the relationship between behavioral similarities and corresponding neural similarity was further explored by using functional magnetic resonance imaging (fMRI; Study 2). Stacking machine learning approach was used to perform predictive analyses of neural activity on consumer behavior both of the self and of friends. Results demonstrate a decrease in behavioral and neural response similarity with increasing social distance within real-world social networks. Furthermore, the similarity undergoes dynamic changes as social relationships evolve. Compared with general stimuli in movie clips, these consumer behavior similarities are reflected in the neural similarities of brain regions, including middle orbitofrontal gyrus, parahippocampal, pallidum, olfactory gyrus, amygdala, calcarine, and superior orbitofrontal gyrus. Moreover, the strength of functional connectivity of these similar brain regions could offer a substantial prediction of both one's own and friends' purchase intention. These findings reflect the phenomenon of endogenous similarity in consumer behavior, and further insight into neural activity sheds light on how shared social experiences influence consumer behavior within social networks.

Materials and Methods

All three studies under consideration characterized the real-world social networks of students from undergraduate in the same class. Study 1A was to test the impact of social distance on the similarity of product evaluation. Study 1B was to investigate dynamic changes in product evaluation similarity as friendships evolved, which was accomplished by testing the same social network 1 year later. Study 2 conducted a naturalistic stimuli fMRI experiment, during which subjects' brain activities were measured while they were watching audiovisual advertisements. The study protocols adhered to the Declaration of Helsinki and were approved by the Key Laboratory of Brain-Machine Intelligence for Information Behavior (BMIB, IRB2023BC034). Prior to the fMRI experiment, written informed consent was obtained from each subject. Each subject received ¥10 in the behavioral study and ¥150 in the fMRI study in compensation for their time.

Study 1A

Behavioral study subjects. Three classes of 175 second-year undergraduate subjects from the same university (mean ± SD 21.9 ± 1.05 year, 106 females) were recruited as subjects. It should be noted that they had been on campus together for one year prior to the behavioral experiment.

Experiment protocol. Study 1 involved a social network survey and a product evaluation task (Fig. 1). The social network survey was designed to assess subjects' positions within the class social network. The task was adapted by many previous studies on social networks (Feiler and Kleinbaum, 2015; Kleinbaum et al., 2015; Burt, 2018). The prompt reads as follows, "Consider the people with whom you like to spend your free time. Since you arrived at [class name], who are the classmates you have been with most often for informal social activities, such as going out for lunch, dinner, drinks, films, visiting one another's homes, and so on?" The response options listed the names of all students in their class, and subjects could select one or more names. To circumvent incomplete or biased recollections, student names were arranged alphabetically by last name, and subjects were reminded that there was no time limit for providing their responses. It is imperative to acknowledge a limitation that the current social network survey was confined to the relationships among these classmates, which potentially underestimates other social connections (familial relationships, other friendships outside the group, etc.).

The product evaluation task was used to assess subjects' liking and purchase intention of a series of products. According to a previous study (Giacalone et al., 2022), subjects were asked to score their level of product liking on a Likert scale ranging from 1 to 7, where 1 indicated the lowest level of product liking and 7 indicated the highest. Likewise, subjects were asked to score the items of purchase intention on a Likert scale ranging from 1 to 7, where 1 indicated the lowest intention and 7 indicated the highest (Xu et al., 2023). Subsequently, subjects were asked to complete the demographic information, such as age, gender, and other relevant details.

Behavioral study stimuli. The choice of new products as the materials of this study was due to the observation that most consumers were less familiar with them, thereby reducing the influence of their prior preference and familiarity (Liu et al., 2020). The products were chosen according to the following steps: (1) 100 products from new product websites (such as https://cn.creative.com) were selected. (2) 100 responders were recruited to scoring on a Likert scale ranging from 1 to 7 (Awan et al., 2021). (3) 40 products with high perceived innovation were screened (mean innovation > 4.29).

Behavioral data analysis. According to the method established in previous studies (Feiler and Kleinbaum, 2015; Kleinbaum et al., 2015), the social networks were characterized by calculating the social distance between each pair of students. By using MATLAB (version 2023b; https://www.mathworks.com/), the social distance in social networks was calculated by the undirected graph that was composed solely of mutually reported social relationships. The relationships between subjects would be divided into different social distances, including friends (social distance = 1), friends of friends (social distance = 2), and nonfriends (social distance = 3). The details are as follows: (1) If both Subject_i and Subject_j report each other as friends, the social distance between Subject_i and Subject_j is 1. (2) If Subject_i and Subject_j both report mutual friendship with Subject_k, but they do not report friendship with each other, the social distance between Subject_i and Subject_j is 2 (friend of friend, e.g., Subject_i – Subject_k – Subject_j). (3) Furthermore, if Subject_i and Subject_j are linked via two intermediaries, the social distance between Subject_i and Subject_j is 3 (nonfriend, e.g., Subject_i – Subject_k –

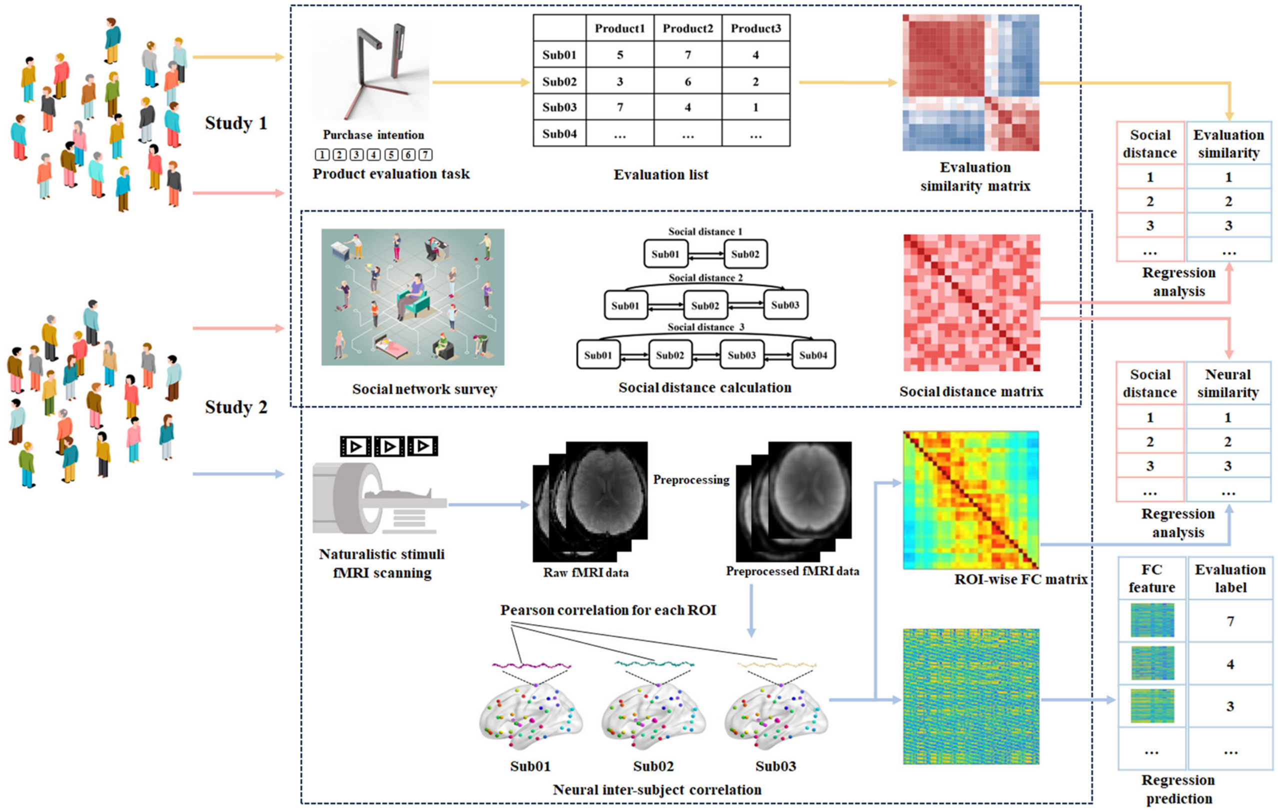

Figure 1. An overall study protocol. Study 1: Firstly, subjects took part in a social network survey and a product evaluation task. Then, the social distance matrix and product evaluation correlation matrices were calculated (see Data Analysis for details). Lastly, the LME model was performed to evaluate the effect of social distance on product evaluation similarities. Study 2: Firstly, subjects took part in a social network survey. Then within 2 weeks after the survey, subjects were informed to participate in the fMRI study, in which they were instructed to passively view a series of product audiovisual advertisements. Thirdly, after the completion of the MRI scanning, subjects filled out demographic information and a questionnaire to assess their purchase intention of each advertised product. Finally, neural similarity analysis and regression prediction were conducted (see Materials and Methods for details). FC, functional connectivity of time series between two brain regions. In the prediction model, the connectivity matrix of seven brain regions of two subjects' dyads were calculated. Then the matrix maps and purchase intention label of each product were obtained (see Materials and Methods). After training with three base models, a stacking meta regressor was obtained to predict test data.

Subject_1 – Subject_j). The unidirectional friendship reports (i.e., where only one subject reported the other as a friend) were excluded from the analysis.

Subsequently, the product liking similarity and purchase intention similarity among social distance were calculated. Despite the collection data from three classes, the structure of social networks remained consistent. Therefore, these three social networks were gathered together for statistical analysis of social distance on product evaluation similarities. According to social network characterization, the dyads (each pair of subjects) were obtained, and the Pearson's correlation coefficient value was calculated based on both their product liking and purchase intention for the series of products (Hyon et al., 2020). The correlation coefficients were Fisher z-transformed to normalize their distribution and serve as a measure of product liking similarity and purchase intention similarity between the two subjects. Finally, the social distance matrix and the product evaluation correlation matrix were obtained. Thereafter, a linear mixed effect (LME) modeling was conducted to evaluate the effect of social distance on product liking similarity and purchase intention similarity, with the Pearson's correlation values as the dependent variable and social distances as the independent variable. The LME model effectively controls false positives by incorporating random effects to account for nonindependence among data points (Chen et al., 2017). To ensure each dyadic relationship was represented only once, dyads were treated as symmetric (i.e., Subjecti–Subjectj and Subjectj–Subjecti were considered equivalent, and only one instance was included per pair). This avoided inflating the number of observations and allowed the degrees of freedom to be estimated based on the number of unique dyads. In addition, the model in this study included a control variable with absolute value of age difference and a binary control variable indicating whether subjects in each dyad were of the same gender. The LME model was conducted by available R package lme4 (Bates et al., 2015) as follows:

$$\text{Product evaluation} \sim \text{Social distance} + \text{Age} + \text{Gender} + (1|\text{Subject}_i) + (1|\text{Subject}_j). \quad (1)$$

Study 1B

Experiment protocol and behavioral study stimuli. Following the completion of Study 1A for 1 year, the same group of 175 subjects was rerecruited to participate the behavioral experiment. The characterization of social networks and product evaluation tasks were identical to those employed in Study 1A. In addition, another 40 new products were added for evaluation to verify the stability of the results.

Behavioral data analysis. Social network characterization and product evaluation similarity analysis were first conducted as Study 1A. Subsequent to the product evaluation similarity analysis, the correlation value of product liking and purchase intention between each pair of subjects in different conditions were extracted. The four types of conditions were as follows: (1) two subjects had not been friends before, but became friends at this time; (2) two subjects had been friends before, but were no longer friends at this time; (3) two subjects had been and still were friends; and (4) two subjects had not been and still were not friends. It should be noticed that nonfriends condition include social distance 2 and 3. Paired t test was conducted to compare the mean differences between two product evaluations (Study 1B vs Study 1A) in these four conditions.

Study 2

fMRI study subjects. Another class of second-year students (all Chinese students, 47 subjects, 33 females) was recruited to participate in this study. All of them completed the social network survey, and 37 of them (mean ± SD 19 ± 0.72 year, 22 females) took part in the fMRI study. All subjects passed the MRI safety screening. No subject reported neurological or psychiatric illnesses or claustrophobia.

Experiment protocol and stimuli. Study 2 involved a social network survey, a naturalistic stimuli fMRI experiment and a postscan questionnaire survey. Firstly, subjects took part in a social network survey, which was consistent with Study 1.

A naturalistic stimuli paradigm of fMRI experiment was employed for the following two reasons. First, dynamic stimuli, as opposed to traditional static stimuli, are more akin to those commonly encountered by subjects in daily lives, and they are likely to engage a relatively large proportion of the emotional and cognitive processes that characterize mental life (Hasson et al., 2010). Second, the natural stimuli paradigm allows subjects' mental processes to unfold without interruption, thereby directly reflecting the relationship between neural activity and behavioral response (Soon et al., 2008).

The fMRI study was conducted within 2 weeks after the social network survey, in which the subjects were instructed to passively view 10 product audiovisual advertisements in a fixed stimuli sequence, with a duration ranging from 40 to 119 s. The fixed stimuli sequence was employed, given that the current study aimed to test the similarity of naturalistic stimuli time series rather than to contrast response to a particular task stimulus. The naturalistic stimuli fMRI study has shown that the fixed stimuli sequence preserves the causal relationships and dynamic cumulative effects between events and enables detection of temporal receptive windows in the human brain (Hasson et al., 2008). Stimuli in randomized order would disrupt the alignment of time series across subjects, introducing additional noise and even potentially obscuring genuine neural synchronization signals (Sonkusare et al., 2019).

The selection of product videos adhered to the following principles according to previous natural stimulation fMRI studies (Hasson et al., 2010; Hasson et al., 2012) and advertising neural response studies (Chan et al., 2019; Chan et al., 2024). Firstly, products with brand effects were avoided. This decision was based on previous studies which extensively documented neural activity differences associated with brand effects (McClure et al., 2004), and strong a priori preferences for brands might introduce unnecessary noise beyond the neural similarity among friends. Secondly, consistent with Study 1, an effort was made to choose video segments that subjects were relatively unacquainted, with the aim to prevent neural activities induced by preference and familiarity. A total of 20 videos were obtained from the creative products website (such as https://www.topys.cn/video). Subsequently, an online pretest was applied to 100 responders to ascertain whether they had viewed the video advertisements, and 10 videos with the averaged lowest viewing rates (< 5%) were finally selected.

After the fMRI scanning, subjects provided demographic information and indicated whether they had previously seen each of the videos. For each video, they responded with a binary choice ("yes" or "no"). Subjects then completed a questionnaire rating their purchase intention for each advertised product on a 7-point Likert scale, where 1 indicated the lowest intention and 7 the highest.

fMRI data acquisition. All MRI data were obtained on a Siemens Magnetom Prisma 3T Scanner (Siemens Healthineers). Comfortable straps and foam pads were used to minimize head motion. A high-resolution T1 anatomical image was scanned for accurate localization with the following parameters: sagittal slices; slice number, 192; matrix size, 256 × 256; field of view (FOV), 256 × 256 mm^2; repetition time/echo time (TR/TE), 2,530/2.98 ms; fractional isotropy (FA), 7°; thickness/gap, 1/0 mm (isotropic voxel size, 1 mm × 1 mm × 1 mm). fMRI images using an echo-planar imaging (EPI) sequence were acquired with the following parameters: TE, 30 ms; FA, 90°; TR, 2,000 ms; 32 slices with interleaved acquisition; thickness/gap, 4/0 mm; FOV, 224 × 224 mm^2; matrix, 64 × 64; and voxel size, 3.5 mm × 3.5 mm × 4 mm.

Behavioral data analysis. The method for constructing the social network was consistent with Study 1 (see Study 1: Data analysis).

Purchase intention similarity: The effect of social distance on purchase intention similarity (see Study 1: Data analysis) was evaluated to repeat the behavioral results of Study 1 from a different stimulus (picture stimulus to video stimulus). There were 223 unique undirected dyads, which derived from the social distances of the 37 subjects involved in the fMRI study. For each dyad, the Pearson's correlation coefficient value was calculated and Fisher z-transformed based on their purchase intention ratings for products presented in advertisement (Zhang and Li, 2012). Then LME model was conducted to evaluate the effect of social distance on the purchase intention similarity.

fMRI data preprocessing. The structural MRI data image was segmented into cerebral cortex, subcortical white matter, deep brain gray matter, and cerebrospinal fluid by using FreeSurfer's recon-all function (Fischl, 2012). After structural image segmentation, the @SSwarper script from AFNI (Cox, 1996; version AFNI_22.3.04) was performed to skull-strip the brain and calculate the warp to standard space. The purpose of structural image processing was to use the generated files for regression of no interest and to normalize functional image into standard space.

The preprocessing of functional MRI data was generated based on the recommendations provided by afni_proc.py by following steps: (1) discarding the first two volumes of functional data to allow the signal to reach equilibrium and the subjects to adapt to the scanning noise; (2) despiking functional data for removing extreme signal fluctuations; (3) shifting voxel time series so that the separate slices were aligned to the same temporal origin; (4) aligning each subject's data to individual structural data by sis-parameter rigid body least squares transformation; (5) registering each subject's functional data to the structural data in standard space; (6) spatial smoothing the data by a 4 mm full-width at half-maximum Gaussian smoothing kernel; (7) scaling each voxel time series to have a mean of 100; and (8) regressing out the regressors of no interest, including signals of white matter, cerebrospinal fluid and head motion parameters. The mask of white matter and ventricle were extracted, based on each subject's FreeSufer segmentation file, and the motion parameters of each subject were extracted during volume alignment. To further investigate the neural mechanisms underlying endogenous similarity, and the relationship between neural similarity and product evaluation, an intersubject neural similarity analysis and a deep learning predictive analysis based on the preprocessing data were conducted. Subsequently, meta-analytic decoding analysis was conducted to further decode the brain similarity map based on variations in each behavioral domain.

Intersubject neural similarity. An intersubject neural similarity analysis was conducted to examine neural similarity differences between friends and nonfriends while subjects were viewing audiovisual advertisements. Intersubject neural similarity was computed as a Pearson's correlation between the fMRI time courses of each two subjects' dyad (Lankinen et al., 2018; Yang et al., 2020). A total of 223 unique undirected dyads were extracted from the social relationships of the 37 subjects involved in the fMRI study (50 friend dyads in social distance 1; 81 friend of friend dyads in social distance 2; 92 nonfriend dyads in social distance 3). Preprocessed fMRI data was segmented into 90 brain regions based on the Automated Anatomical Labeling (AAL) template. Then the single-region intersubject neural similarity was conducted as follows: for each of the 223 dyads, the Pearson's correlation between the time series of fMRI data was calculated for each of the 90 brain regions. A total of 20,070 (223 subject dyads × 90 brain regions) data points were obtained. The correlation coefficients were then Fisher z-transformed to normalize their distribution and treated as the intersubject neural similarity index for each brain region. Social distances across three levels were then compared for each brain region based on these transformed similarity measures. For each of the 90 brain regions, the correlation coefficient was regarded as endogenous similarity index. Finally, a linear mixed-effects (LME) modeling was employed to detect the specific region that caused the effect between social distance and neural similarity, with the social distance (1–3) as the independent variable and correlation values as the dependent variable:

$$\text{Neural similarity} \sim \text{Social distance} + \text{Age} + \text{Gender} + (1|\text{Subject}_i) + (1|\text{Subject}_j). \quad (2)$$

Neural response predicts purchase intention. Regression prediction based on a stacking ensemble machine learning approach (Pavlyshenko, 2018) was performed to test whether the neural response could predict purchase intentions of one's self, friends, and nonfriends. While ISC effectively identifies synchronized regional activities between individuals, it inherently focuses on univariate regional synchrony. In contrast, fMRI functional connectivity explicitly models multivariate interactions between these regions, capturing how coordinated activity across distributed networks, rather than isolated regions, may encode behavioral outcomes (Rogers et al., 2007; van den Heuvel and Hulshoff Pol, 2010). Numerous studies have employed functional connectivity between brain regions as input, in order to graph neural networks for predicting individual behavioral outcomes (Yin et al., 2021; Pei et al., 2023). Consumer behavior involves complex value integration and social inference processes, which possibly depend on cross-regional information transfer. By constructing functional connectivity matrices derived from neural similarity results, the ISC analyses were extended to quantify cross-regional interactions and predict consumer behavior. For each subject, mean time series were extracted for each brain region, and Pearson's correlations followed by Fisher z-transformation were calculated between region pairs (Zhang and Li, 2012). In cross-validation fold, brain regions showing significant similarity among friends were identified within the training set. For each subject, a functional connectivity matrix (e.g., 7×7) based on these regions was computed for each product and used as predictive model features. In the self-prediction model, a dataset of 37×10 (subjects $\times$ products) was obtained, with each subject's purchase intention as the regression label. For friend prediction, 50×10 data points were collected, where 50 represents friend dyads. Similarly, for nonfriend prediction, 50×10 data points were collected, using the nonfriend's purchase intention rating as the label. The Python programming language was used to construct machine learning workflow. Three main algorithms, including random forest (RF), support vector machine (SVM), and backpropagation (BP) from the Scikit-learn package, were used for regression prediction (Li et al., 2023).

The data of three conditions were flattened, transformed from a two-dimensional matrix into a one-dimensional array. With the aim to address potential feature selection bias and ensure rigorous separation between training and testing phases, a nested cross-validation was employed. The entire dataset was divided into five stratified folds, with each iteration reserving 20% of the datapoints as an independent test set that remained completely isolated from all previous analyses. In the remaining 80% training data, brain regions which exhibited significant social distance-related neural similarity were identified exclusively using this training data. Functional connectivity matrices from these regions were then utilized to train the prediction model through an inner cross-validation loop on the training subset, optimizing hyperparameters without exposure to the held-out test data. This process was repeated across all five folds, and the final performance matrices aggregated from predictions on each independent test set. The meta model was trained on this synthesized feature space, learning to optimally combine the predictions of the base models. The performance of the final model was quantitatively assessed by the mean squared error root (RMSE), which represents the degree of derivation between predicted and actual values, and offers insight into the model's predictive accuracy.

SHAP analysis. SHAP analysis is based on game theory and is capable of calculating the contribution of each feature to the model's output. This enables us to determine which brain connectivity features significantly influenced predictions. It was applied to our stacking ensemble model, and the incorporated functional connectivity features thus derived from the seven brain regions identified as significant. The connectivity features were constructed using combinations of Pearson's correlations between brain regions, representing functional interactions relevant to the decision-making processes. SHAP values were subsequently computed for the final ensemble model to determine the average impact of each feature on the model's output. Such interpretability methods have been increasingly utilized to enhance the transparency of predictive models in neural data analysis, which emphasizes the critical role of feature importance in understanding complex neural interactions.

Given the black-box nature of the models under consideration, the TreeExplainer was utilized for Random Forest and gradient-boosted components, and the KernelExplainer for Support Vector Machine and Backpropagation components. The SHAP values were computed for each feature to determine their average contribution to the prediction. The TreeExplainer efficiently calculated Shapley values by taking advantage of the structure of tree-based models, while the KernelExplainer used a sampling-based approach to estimate contributions for nontree-based models.

Meta-analytic decoding. To further decode the brain similarity map based on variations in each behavioral domain, a meta-analytic decoding analysis was conducted to identify which psychological constructs were involved in constructing the neural similarity of viewing audiovisual advertisements. A dataset of term-to-activation mappings provided by the Neurosynth framework (Yarkoni et al., 2011; http://neurosynth.org) revealed the degree of a particular psychological process. The topic-based 80 topics were generated using Latent Dirichlet Allocation modeling of 9,204 fMRI studies (Fox et al., 2014; Sul et al., 2017). Subsequently, the Pearson's correlations between our neural similarity map and each of the 80 topic maps were calculated, and maps that were not related to psychological concepts were excluded (Chang et al., 2012; Chen et al., 2020).

Results

Study 1A

Social network characterization

The social network was first characterized, representing the social relationships within the entire class. The demographic information of three classes is outlined as follows: Class 1 (47 subjects, 28 females, average age $= 20.4 \pm 0.79$); Class 2 (64 subjects, 39 females, average age $= 22.8 \pm 1.13$); and Class 3 (64 subjects, 39 females, average age $= 22.7 \pm 1.23$). Network matrices were calculated to understand the overall structure of the social network and evaluate its functionality and performance (Fig. 2). All three social networks have total 333 social distance dyads, including 184 for distance 1, 88 for distance 2, and 61 for distance 3. The density of the network, defined as the ratio of the number of edges to the number of possible edges, ranges from 0.0303 to 0.0407, indicating the relative sparsity of the network. The dyad-level rate of reciprocity, defined as the probability of mutual reporting connections between pairs of subjects in the presence of any possible nonreciprocal relationships, ranges from 0.3490 to 0.4528, indicating that social relationships in the network tend to be bidirectional. The degree range of a network, defined as the range number of edges connecting nodes, is from 0 to 6, 0 to 5, and 0 to 6, indicating that an individual in social networks will connect with 0 to 6 individuals.

The effect of social distance on product evaluation similarity

In the product evaluation task, subjects were required to rate their liking and purchase intention of each product (Xu et al., 2023). Pearson's correlation coefficient value of product evaluation between each two subjects was then calculated. This coefficient value serves as a measure of product liking similarity and purchase intention similarity between the two subjects. LME model was conducted to examine the effect of social distance on product evaluation similarity, in which the social distances functioned as the independent variable and the Pearson's correlation values as the dependent variable. It revealed a significant effect of social distance on product liking similarity (LME:

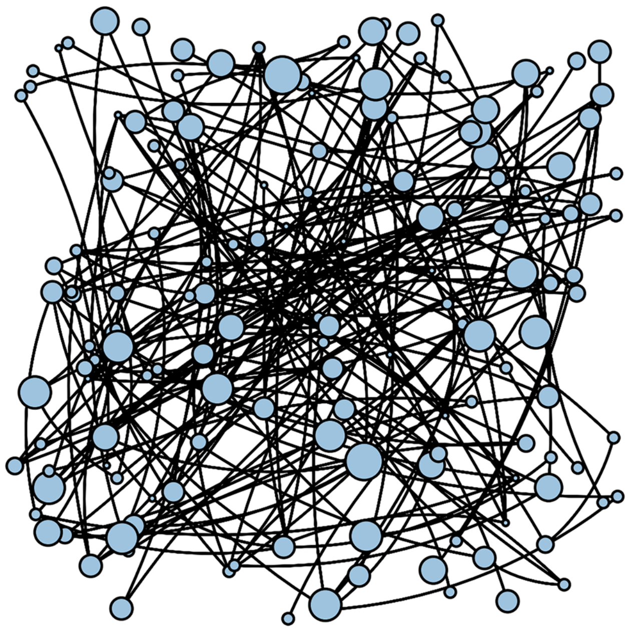

Figure 2. Social networks of three classes ($N = 175$). Nodes indicate students; lines indicate mutually reported social connections among them.

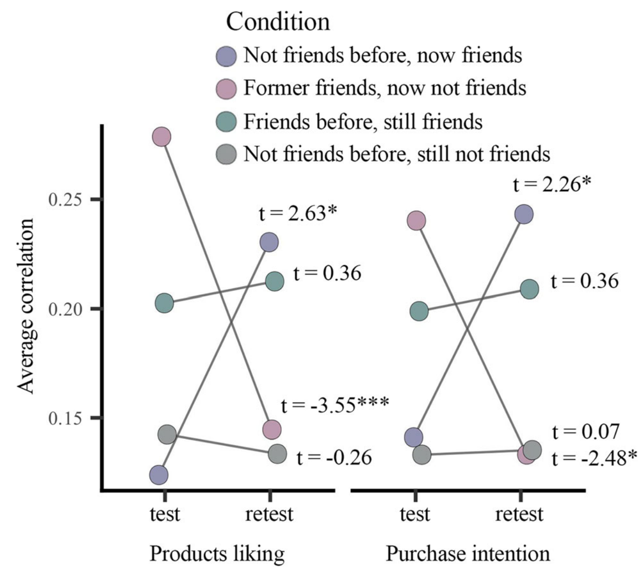

Figure 3. Difference in the mean correlation of product evaluations between two individuals across two studies (Study 1B vs Study 1A). Paired t tests were conducted under four different conditions (not friends before, now friends; former friends, now not friends; friends before, still friends; not friends before, still not friends).

$\beta = -0.04$; $t = -3.07$; $p = 0.002$; $N = 333$; Subject_residual = 0.03) and on purchase intention similarity (LME: $\beta = -0.04$; $t = -2.84$; $p = 0.004$; $N = 333$; Subject_residual = 0.04).

Study 1B

The longitudinal results of social distance on product evaluation similarity

One year after Study 1A, a follow-up study was conducted, encompassing the same 175 subjects and focusing on their social network and product evaluation, with the original and an additional 40 new products (80 total) as materials (see Materials and Methods for details). The data collection and analysis procedures followed the same steps as in Study 1A. The product evaluation similarity results (product liking: $\beta = -0.04$; $t = -2.78$; $p = 0.006$; $N = 333$; Subject_residual = 0.04; purchase intention: $\beta = -0.05$; $t = -3.94$; $p < 0.001$; $N = 333$; Subject_residual = 0.04) show the same significant effect of social distance on product evaluation similarity as Study 1A. The dynamic changes were further assessed in the endogenous similarity of product evaluation as influenced by the structure of social network. The findings reveal that a significant increase in the similarity of product evaluation between individuals who had previously not been friends but now became friends (product liking: $t = 2.63$, $p = 0.012$; purchase intention: $t = 2.26$, $p = 0.029$), while those who had previously been friends but now were no longer friends show a significant decrease in product evaluation similarity (product liking: $t = 3.55$, $p = 0.0008$; purchase intention: $t = 2.48$, $p = 0.016$). There was no change in similarity of product evaluation between individuals who remained friends or non-friends (Fig. 3).

Study 2

Social network characterization

An fMRI study was conducted to reveal the neural basis underlying endogenous similarity of consumer behavior, and it involved a social network survey, a naturalistic stimuli fMRI experiment and a post-scan questionnaire survey (see Materials and Methods and Fig. 1 for further details). All 47 students in a class accomplished the social network survey, and 37 of them took part in the fMRI experiment. The network has 223 social distance dyads, including 50 for distance 1, 81 for distance 2, and 92 for distance 3. The density of the network is 0.0691. The dyad-level rate of reciprocity is 0.4582. The degree range of network is from 0 to 11 (mean = 3.25, SD = 2.04, median = 3), which reveals the strong connections of core node.

The effect of social distance on purchase intention similarity

During the fMRI experiment, each subject passively viewed a series of product audiovisual advertisements (10 clips total; see Materials and Methods for further details). Responses indicated that the majority of subjects (31 out of 37) had not previously seen any of the advertisements shown during the fMRI study. Across all trials, only 8 out of 370 video exposures (2.2%) were reported as previously viewed.

Following the fMRI scanning, each subject completed a post-scan questionnaire survey to report their purchase intention of each product that was presented in scanning. LME model reveals a significant effect of social distance on purchase intention similarity ($\beta = -0.11$; $t = -3.84$; $p < 0.001$; $N = 223$; Subject_residual = 0.11).

The effect of social distance on neural similarity

The intersubject similarities in neural responses were assessed during subjects' viewing of audiovisual advertisements among social distances. Spanning the course of the entire experiment, mean response time series were extracted from 90 brain regions for each of the 37 fMRI study subjects. For each of the 223 unique dyads, the Pearson's correlation between the time series of brain responses was calculated for each region. To test the relationship between social distance and neural similarity, the LME model was conducted, in which the social distances was designated as the independent variable and the Pearson's correlation values of brain region as the dependent variable. Illustrated in Figure 4*A*,*B*, the average relative level of neural similarity among dyads within social distance (1–3) was examined for each AAL (Anatomical Automatic Labeling) brain region. Figure 4*C* and Table 1 demonstrate the LME results for each of 90 ROIs. The results show that the neural similarity is associated with friendship in regions of middle orbitofrontal gyrus ($p = 0.003$), parahippocampal ($p = 0.038$), pallidum ($p = 0.045$), olfactory gyrus ($p = 0.045$), amygdala ($p = 0.053$), calcarine ($p = 0.054$), and superior orbitofrontal gyrus ($p = 0.063$).

Purchase intention prediction

The study subsequently sought to ascertain whether it was possible to predict purchase intention of one's self and friends based on the functional connectivity maps during the viewing of video advertisements.

To enhance the model robustness and accuracy of the model in predicting brain connectivity features, a stacking ensemble machine learning approach was employed to leverage the diversity of base learners and meta-model retraining to improve generalization. The approach includes random forest (RF), support vector machine (SVM), and backpropagation (BP; see Materials and Methods for further details). Each learner independently assimilated patterns from the input features and formed individual predictors. Once the base learners generated predictions, these outputs were fed into a meta-regressor in the second stage. The task of the meta-regressor was to combine the predictions from the three different learners to yield the ultimate output. The data of three conditions were flattened and transformed from a two-dimensional matrix into a one-dimensional array. The data were thereby partitioned into training and testing sets, with 80 and 20% of the data allocated, respectively. Finally, the stacking ensemble learning with fivefold cross-validation was conducted with outputs of these models, and a meta-linear model was thus trained in a secondary learning phase to produce the final prediction.

RMSE was employed as an indicator to evaluate the accuracy of model predictions. A reduced value of RMSE corresponds to a diminished average error of model predictions. As shown in Figure 5, the prediction RMSE of meta-regressor for three conditions were self (RMSE = 0.56), friends (RMSE = 0.73), and nonfriends (RMSE = 2.08). To compare the differences of prediction errors, the absolute prediction error was calculated and two-sample t tests between each two conditions were conducted. There was significant difference between the self and friends ($t = -3.99$, SD = 0.53, $p < 0.001$), between the self and nonfriends ($t = -12.90$, SD = 0.93, $p < 0.001$), and between friends and nonfriends predictions ($t = -11.76$, SD = 0.91, $p < 0.001$).

SHAP analysis

To quantify the contribution of each functional connectivity feature to predicting purchase intentions in both the self and friends in the stacking ensemble model, an interpretability analysis was conducted using SHAP (SHapley Additive

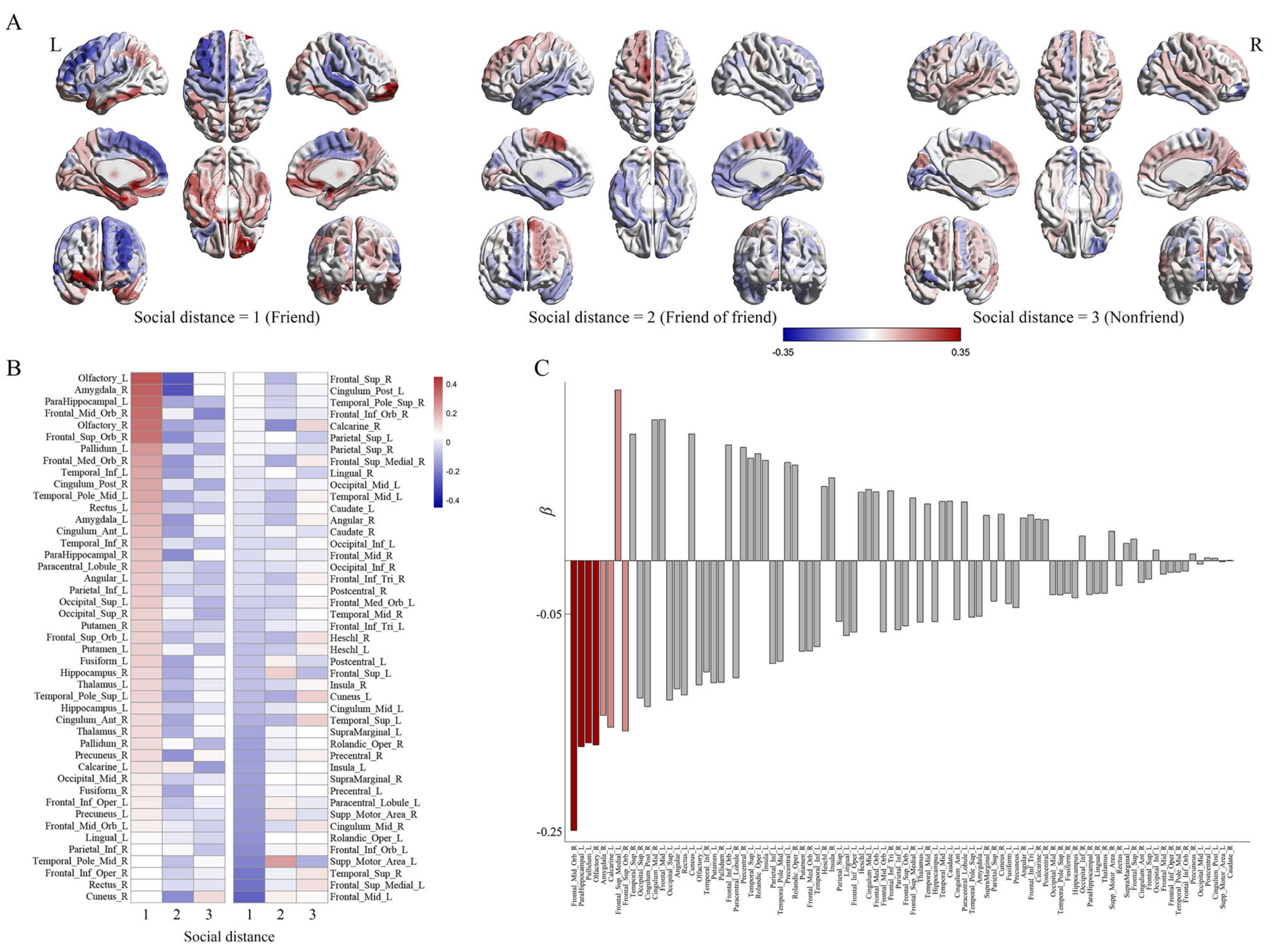

Figure 4. ***A***, The intersubject neural similarities for each brain region of friends and nonfriends. Intersubject correlations of neural response time series for each dyad were obtained from AAL template for regions of interest (ROIs). Warmer colors indicate relatively similar neural responses for a given brain region; cooler colors indicate relatively dissimilar neural responses for that brain region. ***B***, Intersubject neural similarities of friends and nonfriends, with average dyadic fMRI response time series similarities overlaid on a cortical surface model. ***C***, Testing associations between social distance and neural similarity. As described in the main text, LME models were carried out for each brain region in which social distance (1–3) were modeled as a function of local neural similarities. Negative coefficients for neural similarity indicate that greater neural similarity was associated with friends.

exPlanations). As shown in Figure 6, it reveals that in self-prediction the connections between Frontal_Mid_Orb_R - Pallidum_L (0.161), Pallidum_L - Olfactory_R (0.137) and Pallidum_L – Calcarine_L (0.126) exhibit high mean SHAP values. The most influential functional connectivity features in terms of the friend prediction condition are the connections between Parahippocampal_L - Pallidum_L (0.126) and Frontal_Mid Orb_R – Olfactory_L (0.118).

Meta-analytic decoding

The meta-analytic decoding was conducted to further reveal the association between neural similarity and cognitive function. The results manifest the correlation between psychological construct maps and neural similarity maps in the process of subjects' viewing of audiovisual advertisements, during which intersubject similarity brain map among friends showed stronger associations with the object perception ($r = 0.39$), attention ($r = 0.30$), memory ($r = 0.21$), social judgment ($r = 0.19$), and reward ($r = 0.12$) topic maps (Fig. 7). These results indicate that olfactory gyrus, amygdala, and middle orbitofrontal gyrus are important components in psychological process maps of watching audiovisual advertisements. It is consistent with our intersubject correlation analysis.

Table 1. LME model results of social distance on neural similarity

Hemi	Region	β	p
R	Frontal_Mid_Orb	−0.253	0.003
L	ParaHippocampal	−0.174	0.038
L	Pallidum	−0.170	0.045
R	Olfactory	−0.173	0.045
R	Amygdala	−0.145	0.053
L	Calcarine	−0.156	0.054
R	Frontal_Sup_Orb	−0.159	0.063

β denotes regression coefficients, indicating that closer social relationship is associated with greater neural response similarity. Hemi denotes hemisphere; L, left; and R, right.

Discussion

The current study conducted three experiments in real-world social networks to investigate endogenous similarity in product evaluation, its related neural mechanisms, and prediction of neural activity on purchase intention. The results show that product evaluation exhibits a high degree of similarity among friends and undergoes dynamic changes in response to the alterations in the structure of social networks. Furthermore, neural similarity in brain regions, such as olfactory gyrus, amygdala, parahippocampal gyrus, orbitofrontal cortex, superior frontal gyrus, pallidum, and posterior cingulate gyrus, manifests a heightened neural synchrony among friends, which is associated with cognitive functions like object perception, attention, memory, social judgment, and reward processing. More importantly, prediction analysis based on machine learning shows that individual's neural response to audiovisual advertisements

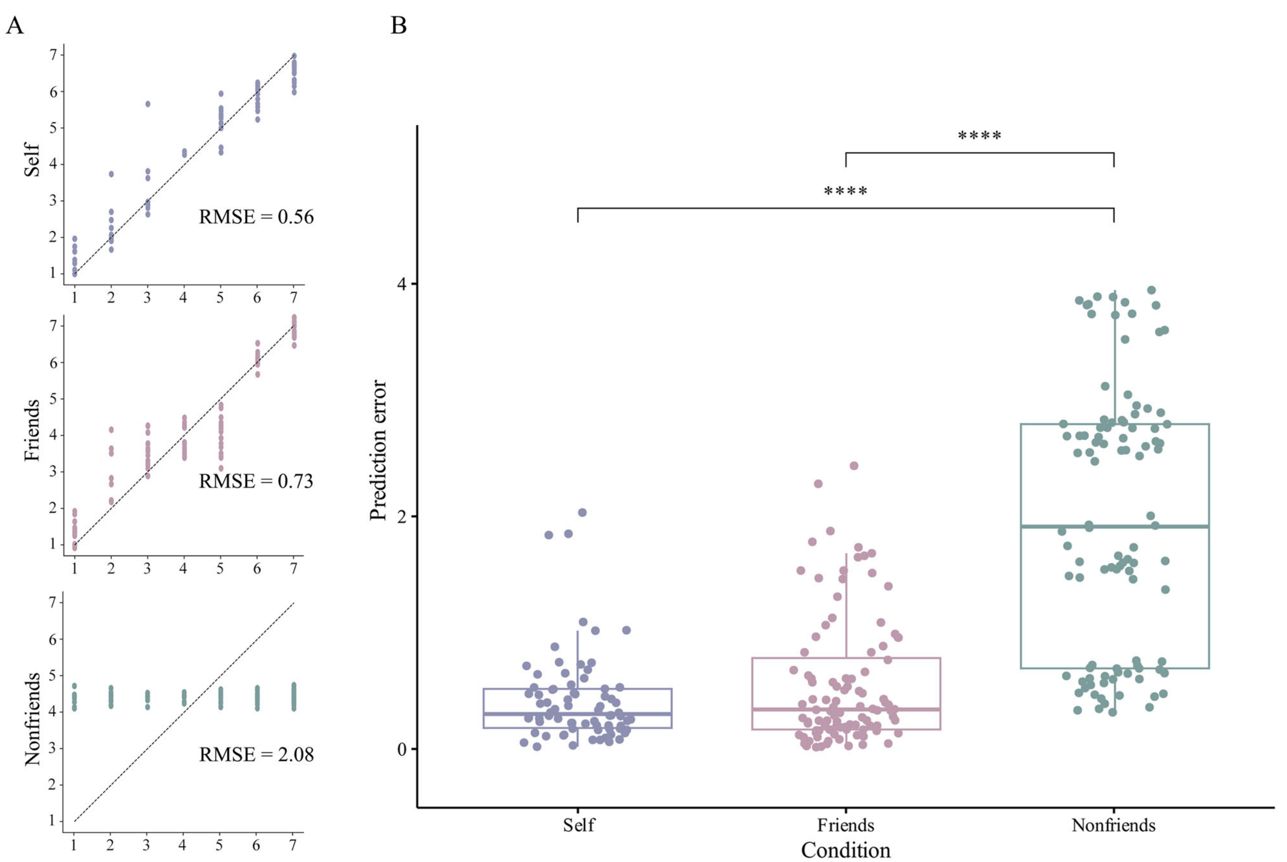

Figure 5. ***A***, Results of the true value and prediction value of each predictive sample under three conditions. The *x*-axis represents the true purchase intention value and *y*-axis represents the predicted purchase intention value for each sample. ***B***, Plots of prediction error of each condition. The central line inside each box represents the median prediction error for that condition. The top and bottom edges of the boxes represent the first quartile (Q1) and the third quartile (Q3), respectively. Points outside of this range are displayed as individual outliers. *t* test results display significant difference between the self and friends, between the self and nonfriends, and between friends and nonfriends prediction. **** indicates that the effect is significant at the level of 0.0001.

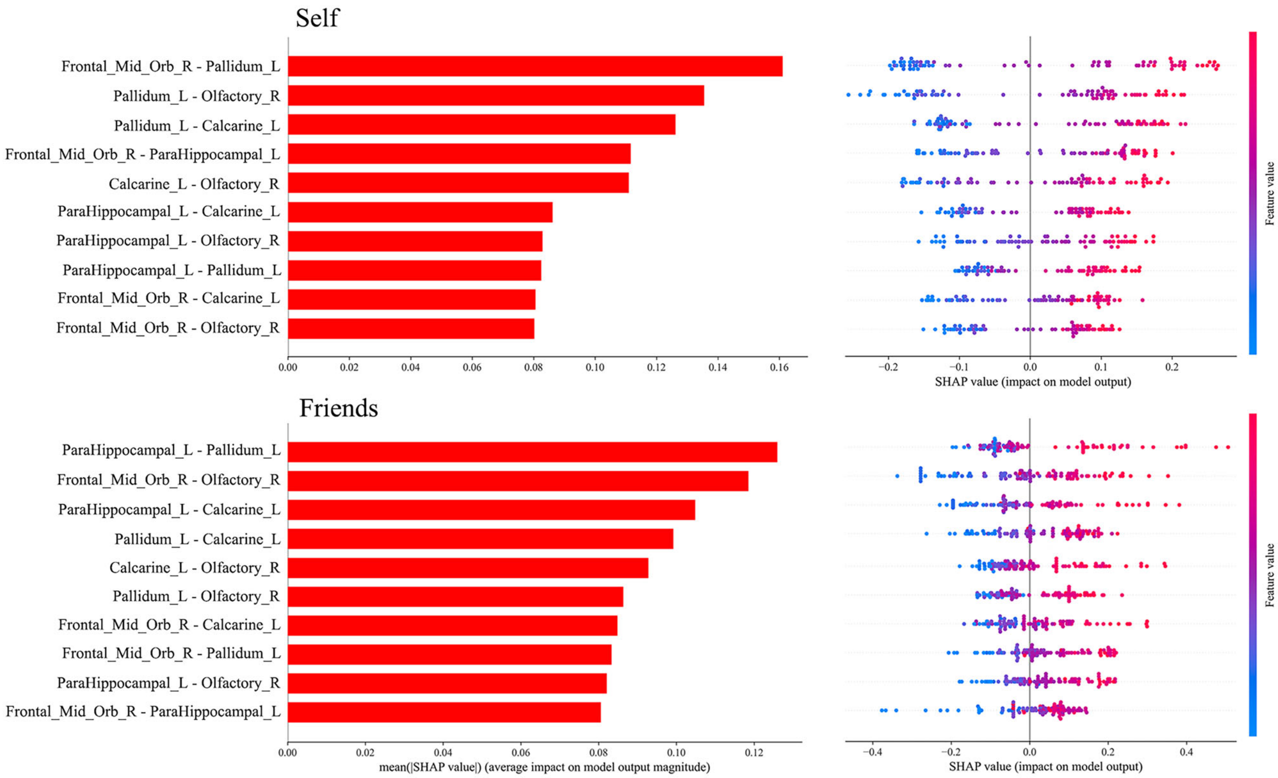

Figure 6. SHAP results of the self and friends prediction conditions. ***A***, The mean SHAP value average impact on model output for the self (left) and friends (right) conditions of each functional connectivity feature. ***B***, The SHAP values of features in every sample. Each line represents a feature, and each dot visualizes the SHAP value for one subject and its corresponding feature. The vertical axis represents both the features, ordered by the mean absolute SHAP values and their distribution.

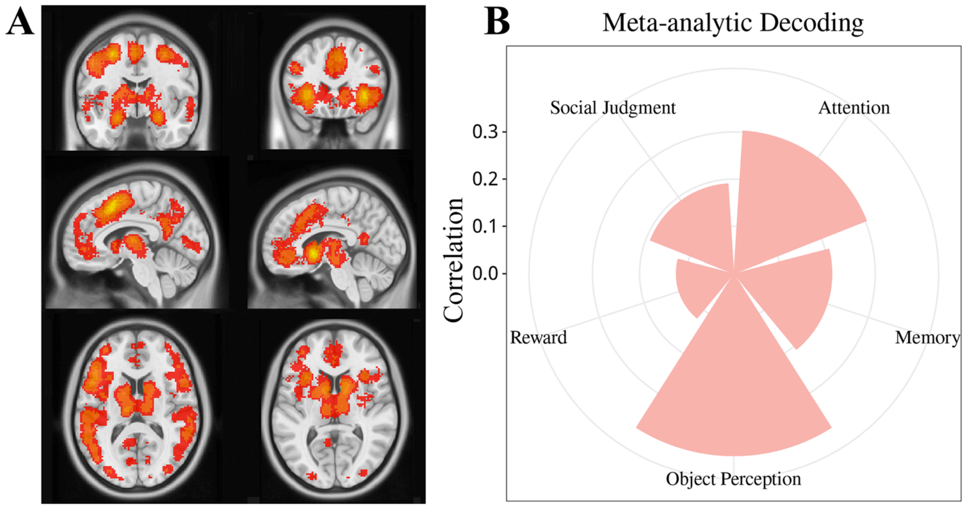

Figure 7. ***A***, Thresholded topic-based maps of object perception (left) and reward (right). ***B***, Polar plot of the strength of association between each topic and neural similarity map.

can predict not only their own purchase intentions but also those of their friends, while this predictability does not extend to nonfriends.

The behavioral results indicate that the similarity of products evaluation in social networks is similar among friends, and the similarity decreases as social distance increases. This similarity will dynamically change with social distance. That is to say, individuals with social relationships, even not influenced by friends, still share similar product liking and purchase intentions. These results are consistent with previous studies that friends in social networks are more likely to share similar thoughts and behaviors (Dehghani et al., 2016; Smith et al., 2018; Ehlert et al., 2020). This may be attributed to the fact that friendships are often grounded in shared values, interests, and experiences (Parkinson et al., 2018), which in turn fosters consistency in product evaluations.

However, the majority of the previous studies focused on the similarity of feelings, emotions, and cognition, rather than on specific behavioral performances that carry individual preference characteristics. Consumer behavior, conversely, involves unique dynamics of the expression of identity and self-presentation, since individuals frequently use consumer choices as a means to signal aspects of personal identity and differentiate themselves within social contexts (Otto et al., 2022). In addition, previous studies focused solely on the current state, neglecting the dynamic tracking of changes in behavioral similarity following shifts in social distance. This resulted in a limited understanding of how behavior converges or diverges over time as social distance fluctuates (Baek et al., 2022). In the current study, it is revealed through longitudinal behavioral studies that product evaluation similarity between individuals varies significantly with changes of social distance in real-world social networks. The behavioral results have made significant contributions to the theory of endogenous similarity, and the current study is the first to demonstrate the impact of social distance on product evaluation similarity in real-world social networks and its dynamic effects.

The other major contribution of the current study is the finding of the neural mechanisms underlying endogenous similarity of product evaluation in real-world social networks. Brain regions exhibit significant neural similarity among friends during the viewing of product advertisements. These regions include cortical areas such as the middle orbitofrontal gyrus and parahippocampal, as well as subcortical regions like the ventral pallidum and amygdala. These findings are consistent with, yet meaningfully extend, the previous studies on neural similarity. For instance, Parkinson identified neural similarity in regions associated with attentional allocation (e.g., superior parietal lobule), narrative interpretation (e.g., inferior parietal cortex), and affective processing (e.g., amygdala, nucleus accumbens, and caudate nucleus; Parkinson et al., 2018). While both of Parkinson's and this study are involved in shared emotional and reward-related circuitry (e.g., amygdala, ventral striatum), this study uniquely highlights regions that are tied to consumer-specific behaviors, such as the middle orbitofrontal gyrus, a hub for value coding, purchase intention, and decision-making (Kringelbach, 2005), and the parahippocampal, which supports memory integration and contextual associations during product evaluation (Aminoff et al., 2013).

Furthermore, results from subcortical regions reveal specific behavioral similarities emerging from consumer behavior processing. Although these areas exhibit robust responses in general contexts, they may engage distinct functional roles during the evaluation of consumption-related stimuli. The ventral pallidum has been demonstrated to serve as an important limbic final common pathway for processing of reward and motivation (Smith et al., 2009). The amygdala was considered a pivotal center in processing emotional information, and a fundamental piece of the neural machinery controlling sociosexual behaviors (Olucha-Bordonau et al., 2015). These results suggested that the product evaluation similarity is driven by cognitive function, such as sensory processing (Wu and Chen, 2024), value coding (Kringelbach, 2005), and decision-making behavior (Kühn et al., 2016). This is consistent with our meta-analytic decoding results, which find that intersubject similarity brain maps among friends reveal stronger associations with the object perception, attention, memory, social judgment, and reward processing topic maps. These regions play a significant role in how individuals perceive and evaluate products, as they integrate visual information with memory and emotional responses to drive purchase intention choices.

Previous studies have demonstrated the predictability of neural activity in individual behavior (Genevsky et al., 2017). However, based on the significant neural similarity between individuals in close relationships within real social networks, the current study further reveals the predictive power of neural activity in predicting the behavior of friends. The functional connectivity of brain regions, which exhibit significant similarity in product evaluation among friends, not only predict individual's own purchase intention but also the purchase intentions of their friends. SHAP analysis results show that in terms of self-purchase prediction, emotional regulation and memory-related processing play critical roles, and involvement of reward and motivational pathways in decision-making processes is also highlighted. In terms of friend prediction, the important connections indicate the involvement of integrative sensory processing and higher cognitive functions in decision-making. The consistency between the predictive analyses and behavioral performance underscores the correlation between regional brain activity and behavioral performance and offers new insights into the interplay between brain activity and behavioral dynamics within social networks.

A comprehension of the endogenous factors that underpin social relationships and corresponding consumer behavior has its significant implications for marketing strategies. First, the endogenous similarities among friends exists in their consumption behavior. In intelligent recommendation algorithms, such as precision marketing (You et al., 2015), personalized recommendation (Behera et al., 2020), and intelligent recommendation (Li et al., 2020), it is possible to enhance the effectiveness of these technologies by not only considering the user's own historical data but also by taking into account the circumstances of closely connected individuals within the user's social networks. Second, endogenous similarities are driven by specific brain regions according to fMRI results. Therefore, by enhancing the characteristics of perceived content, value, and emotion of advertisements, marketing efficiency could be improved by strengthening the behavioral similarities among users within social networks. For instance, when marketing to a group of individuals, increasing the attractiveness of advertisements by enhancing these characteristics can significantly improve marketing efficiency and effectiveness.

While the current study contributes valuable insights, it is not without limitations. The subject pool is predominantly composed of second-year students. It is advantageous to this study since they have already formed a real and robust social network. However, it still limited the generalizability of the findings. Future research could include a more diverse sample to enhance the external validity of the results. Additionally, although the naturalistic stimuli paradigm was employed to align with consumers' daily lives, it is still unable to fully capture the intricacy and complexity of real-world consumer decisions. An expanded exploration of alternative stimulus paradigms and consumer characteristics could provide a more comprehensive understanding of consumer behavior.

In conclusion, the current study aims to investigate the endogenous similarity of consumer behavior and the underlying neural mechanism in real-world social networks. In our findings, friends within real-world social networks manifest remarkable similarity in terms of product evaluation, which is dynamic and changeable with the social distance between individuals. The neuroscientific results show that friends exhibit a heightened neural synchrony in brain regions that are involved with sensory processing, value coding, purchase intention, and buying decision. These brain activity data also demonstrate its potential to predict their own or friend's purchase intention. The findings of our study contribute to understanding the fundamental theory of product evaluation and provide a theoretical basis for the formulation of marketing strategies. Furthermore, the integration of neural similarity analysis, meta-analytic decoding, and deep learning-based prediction models exemplifies a novel methodological approach that can be applied to other domains within psychology and neuroscience. This approach can enhance the ability to predict complex social behaviors and offer new avenues for exploring the neural basis of social influence and decision-making.

Data Availability

The data that support the findings of this study and the code used for the analyses are available from the corresponding author upon request.

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