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Screening social anxiety with the Social Artificial Intelligence Picture System

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A R T I C L E I N F O

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A B S T R A C T

Social anxiety disorder (SAD) is a prevalent anxiety disorder marked by strong fear and avoidance of social scenarios. Early detection of SAD lays the foundation for the introduction of early interventions. However, due to the nature of social avoidance in social anxiety, the screening is challenging in the clinical setting. Classic questionnaires also bear the limitations of subjectivity, memory biases under repeated measures, and cultural influence. Thus, there exists an urgent need to develop a reliable and easily accessible tool to be widely used for social anxiety screening. Here, we developed the Social Artificial Intelligence Picture System (SAIPS) based on generative multi-modal foundation artificial intelligence (AI) models, containing a total of 279 social pictures and 118 control pictures. Social scenarios were constructed to represent core SAD triggers such as fear of negative evaluation, social interactions, and performance anxiety, mapping to specific dimensions of social anxiety to capture its multifaceted nature. Pictures devoid of social interactions were included as a control, aiming to reveal response patterns specific to social scenarios and to improve the system's precision in predicting social anxiety traits. Through laboratory and online experiments, we collected ratings on SAIPS from five dimensions. Machine learning results showed that ratings on SAIPS robustly reflected and predicted an individual's trait of social anxiety, especially social anxiety and arousal ratings. The prediction was reliable, even based on a short version with less than 30 pictures. Together, SAIPS may serve as a promising tool to support social anxiety screening and longitudinal predictions.

1. Introduction

Social anxiety disorder (SAD) is a prevalent and disabling psychiatric condition characterized by intense fear and avoidance of social situations (Rozen & Aderka, 2023; Stein & Stein, 2008). Typically emerging in adolescence and persisting into adulthood, SAD significantly disrupts daily functioning (Suhas et al., 2023). Globally, its prevalence varies, with rates as high as 36 % among young adults in diverse cultural and economic contexts (Jefferies & Ungar, 2020). Broader epidemiological data estimate 30-day, 12-month, and lifetime prevalence at 1.3 %, 2.4 %, and 4.0 %, respectively, with higher rates in high-income countries and younger populations (Stein et al., 2017).

SAD is associated with an increased risk of developing major depressive disorder and substance abuse (meta-analysis, Clauss & Blackford, 2012; Kalin, 2020), more severe eating disorder psychopathology (meta-analysis, Kerr-Gaffney et al., 2018), substance dependence, suicide attempt, and suicide risk (meta-analysis, Leigh et al., 2023), leading to debilitating effects on patients' lives and work.

1.1. Screening challenges for SAD

Early detection of SAD lays the foundation to introduce early cognitive behavioral interventions, which have shown promising effects on SAD (Caletti et al., 2022; Clark et al., 2003; Guo et al., 2021). Despite the importance of early detection of SAD, the screening for social anxiety (SA) based on clinical interviews is challenging given the nature of social fear and avoidance of SAD, as patients do not turn to professional help unless due to comorbid physical or mental health problems (Goetter

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et al., 2020). Moreover, SA further complicates clinical assessments by preventing patients from engaging in diagnostic interviews or participating fully in clinical evaluations, which are themselves anxiety-provoking (Letamendi et al., 2009).

Traditional diagnostic tools, such as the Anxiety Disorders Interview Schedule (ADIS-IV) and the Structured Clinical Interview for DSM-IV (SCID-I/P), are comprehensive but resource-intensive, requiring trained professionals and posing logistical challenges for large-scale screening (Letamendi et al., 2009), and therefore highlights the need for accessible, scalable, and less anxiety-inducing methods, such as self-administered measurements.

Nevertheless, classic questionnaires also have notable limitations, despite their practicality for standardized data collection and easy deployment. For instance, Liebowitz Social Anxiety Scale (Mennin et al., 2002) is recognized for its comprehensive evaluation of fear and avoidance dimensions, effectively distinguishing psychological and behavioral aspects, but criticized for its length and lack of items addressing cognitive schemas or physiological symptoms. Social Phobia Inventory (Connor et al., 2000), in contrast, is more concise and includes avoidance measures, though its narrower scope may not fully capture the complexity of SAD symptoms. Additionally, questionnaires bear the limitations of subjectivity, memory biases under repeated measures, and cultural influence, compromising data quality and accuracy, especially for repeated measures in longitudinal studies. Therefore, there is an urgent need to call for accessible and convenient tools that can be widely used online and offline to facilitate early social anxiety screening.

Given these limitations, alternative approaches, such as visual stimuli depicting social scenarios, may provide a more engaging and less biased method for early SAD detection. Several classic affective picture databases exist, such as the International Affective Picture System (IAPS, Lang et al., 1997), the Geneva Affective Picture Database (GAPED, Dan-Glauser & Scherer, 2011), and the Nencki Affective Picture System (NAPS, Marchewka et al., 2014; Riegel et al., 2016). However, these databases primarily focus on general emotional reactions and lack the specificity needed for social scenarios that are critical for accurately assessing social anxiety. They are not designed to depict social interactions, body language, or interpersonal contexts that reflect the theoretical constructs underlying social anxiety. In addition, image databases focused on facial expressions, such as the Chinese Affective Face Picture System (CAFPS), provide facial emotional stimuli but lack contextual cues of social scenarios. As a result, none of the aforementioned databases were specifically designed to depict social scenarios and reflect the constructs underlying social anxiety, and it is rare to find picture databases specifically targeting social anxiety.

1.2. Addressing limitations of traditional screening methods with AI

To generate diverse social scenarios, we adopted state-of-the-art diffusion generative Artificial Intelligence (AI) models that generate realistic pictures from natural language prompts. Compared to traditional image databases, AI-generated database offer several advantages.

First, AI-generative models enable the creation of diverse, contextually relevant social scenarios. These models allow for variations in critical elements, such as social relationships, gender, age, race, environment (indoor vs. outdoor settings), and the number of agents involved. This flexibility ensures a broader representation of social interactions, which is difficult to achieve with traditional, static image databases. Second, AI-generative pictures achieve high realism while controlling for irrelevant low-level visual features (e.g., specific facial characteristics, accessories, or background elements) that could introduce bias. By focusing on key social cues, AI-generated pictures provide more consistent and reliable participant responses. Finally, the use of AI-generated images avoids copyright issues related to depicted individuals, offering flexibility from both legal and ethical perspectives.

AI and machine learning (ML) offer innovative solutions for mental health diagnostics, addressing traditional limitations with enhanced detection and measurement (Huckvale et al., 2019). Reviews show their effectiveness in early stress detection, large-scale monitoring, and personalized mental health screening (Liu et al., 2024). Meta-analyses highlight their use in perinatal mental health for identifying risk factors and predicting disorders (Kwok et al., 2024). Building on these advancements, AI-generated social scenarios and ML algorithms provide scalable and culturally adaptive tools for early and accurate detection of SA traits.

1.3. The present study

In the current study, we introduce the Social Artificial Intelligence Picture System (SAIPS), which consists of 279 model-generated realistic and high-quality social pictures developed following theoretical constructs of social anxiety, and 118 control pictures without human social information. In three laboratory and online experiments, we collected ratings of social anxiety rating (SAR), valence, arousal, involvement, and picture-text consistency for each picture. We aim to examine whether SAIPS can serve as a robust tool to detect SA trait, both in laboratory settings and in online surveys. Furthermore, we aim to use explainable ML algorithms to predict concurrent and one-month follow-up SA traits based on a short version of SAIPS to examine the robustness and the generalization ability of social anxiety screening based on such a database.

2. Experiment 1: laboratory examinations of SAIPS ratings

In Experiment 1, we conducted laboratory experiments to examine the clusters of SAIPS pictures, and to investigate whether ratings of SAIPS pictures can be used as predictors of concurrent and one-month follow-up SA traits.

2.1. Methods

2.1.1. Participants

Based on the power analysis guidelines (Lakens, 2022), the sample size was calculated using G*Power based on a partial eta-squared of 0.07 from prior research (Heuer et al., 2010). The required sample size was 57, for a MANOVA with three groups (high/medium/low SA traits), five-dimensionalmeasures, α of 0.05, power of 0.80, and correlations of 0.25. The sample sizes for Exp 1, 2a, and 2b were 59, 121, and 126 respectively, ensuring adequate statistical power.

Fifty-nine participants (29 females, age: $M = 22.1$, $SD = 3.07$) were recruited into the study. Participants were naive to the purposes of the experiment, had normal or corrected-to-normal vision, and had no known neurological or visual disorders. Participants were provided with written informed consent in accordance with the procedures and protocols approved by the human subject review committee of Peking University. Participants were compensated with 65 RMB for their participation. The research protocol was preregistered on the Open Science Framework (OSF) at osf.io/zh7jd. The participant recruitment process was detailed in Supplemental material S1.

2.1.2. Stimuli

A total of 118 pictures depicting social scenarios were generated by AI generative models, including Stable Diffusion-XL (Podell et al., 2023) and DALL-E 2 (Ramesh et al., 2022). The scenes depicted in the pictures were constructed based on the theoretical framework of social anxiety (Morrison & Heimberg, 2013; Spence & Rapee, 2016) and existing questionnaires (e.g., SAQ-A). The details on the development and validation of the AI-generated stimuli can be found in Supplemental material S2.

Pictures were generated along three theoretical dimensions grounded in existing SA-related theories: (1) Emotional expression: negative, neutral, or positive expression (Keltner et al., 2019); (2) Social dominance: with dominant individual (i.e., one agent presenting a sense of being more important or stronger than other agents in the picture, or than the observer) presented, or otherwise (e.g., peer-like relationship, or a single agent) (Bergh et al., 2020; Lease et al., 2002); and (3) Eye contact: with eye contact, or without eye contact (Schneier et al., 2011). Prompts were crafted based on these dimensions and were entered into AI generative models for picture generation. Post-generation, pictures were manually refined to adjust for distorted facial expressions or body parts (e.g., disproportional hands) and were uniformly resized to 1024 × 768 pixels (see Fig. 1 for examples). Inclusion criteria for pictures were: 1) Alignment with the three dimensions; 2) Depiction of characters engaged in specific social activities (e.g., public speaking, conversing with strangers, expressing anger); 3) Clear figure-ground distinction, ease of interpretation, and rapid identification of the emotional content.

2.1.3. Procedure

The stimuli were presented through Matlab R2022b and the Psychophysics Toolbox on computers. The presentation order of the pictures was randomly assigned to participants. Each picture was presented with no time limit.

Ratings were collected from five perspectives: social anxiety rating (SAR), valence, arousal, involvement, and picture-text consistency. Each dimension was rated from 1 to 9. For valence, 1 indicated very negative, and 9 indicated very positive; for the other dimensions, 1 indicated a low level (e.g., low arousal), and 9 indicated a high level (e.g., high arousal). Specifically, SAR measures anxiety evoked by the pictures, and is consistent with a subscale of SAQ-A (Caballo et al., 2012). Valence captures emotional reactions, highlighting negativity biases in social anxiety (Miers et al., 2020). Arousal reflects emotional intensity, with socially anxious individuals showing stronger responses to perceived social threats (Grisham et al., 2015). Involvement assesses the perceived immersion in social situations, reflecting the excessive engagement with social threats and heightened personal relevance in SAD (Wells et al., 2016). Finally, picture-to-text consistency evaluates how well the image matches the description, with inconsistencies potentially amplifying cognitive biases in SAD (Constans et al., 1999), reflecting sensitivity to social ambiguity.

To ensure participants' comprehension of the five rating dimensions, the variables' definitions to be tested were first elucidated, followed by five practice questions to clarify the meaning of each dimension of ratings. For example, participants received the explanation that social anxiety refers to "an emotional state of feeling uneasy or fearful in social situations"; valence represents "the degree to which you feel unhappy (negative emotion) or happy (positive emotion) internally after seeing a particular image"; arousal refers to "the level of excitement you feel internally after seeing a particular image"; involvement refers to "how vivid, detailed, and lifelike you can feel as if you are immersed in the scene depicted in the image"; and picture-text consistency refers to "the level of consistency and relevance between an image and its corresponding text description." Then, participants went through a practice to familiarize themselves with the five rating dimensions. In the practice, straightforward exemplars were presented for participants to rate. The formal rating block included 118 trials. Participants were granted a 1-minute rest after completing every 30 trials.

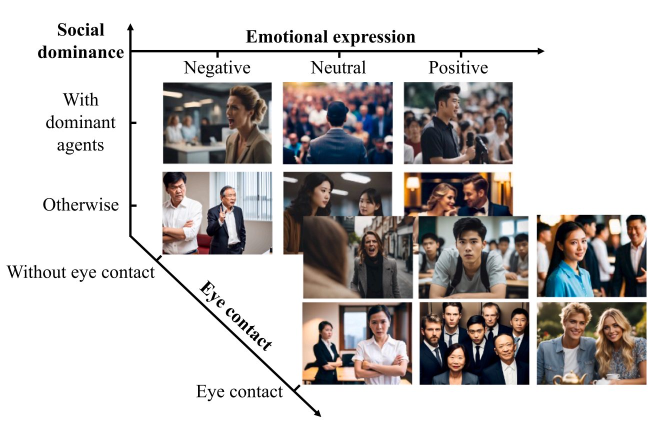

Fig. 1. SAIPS picture examples from three theoretical construction dimensions: emotional expression: negative, neutral, or positive; social dominance: with dominant individual, or otherwise; and eye contact: with eye contact, or without eye contact.

2.1.4. Measures

SA traits were measured through the Chinese Social Anxiety Questionnaire for Adults (CSAQ-A, Wang et al., 2024) after the rating task. CSAQ-A consisted of 30 items and evaluated SA traits by delineating five dimensions divided by social situations: authority, opposite gender, expressing displeasure, being criticized, and stranger dimensions. An example item is "Greeting someone and being ignored." Response options were provided on a 5-point Likert-type scale (1, Not at all or very slightly; 5, Very high or extremely high).

CSAQ-A demonstrates strong psychometric properties in Chinese populations (Wang et al., 2024), with high internal consistency (Cronbach's $\alpha = 0.96$) and test-retest reliability ($r = 0.80$). Criterion-related validity is supported by significant positive correlations with established SA measures, such as Liebowitz Social Anxiety Scale, Brief Fear of Negative Evaluation Scale, and Penn State Worry Questionnaire (ICC = 0.40–0.67, $ps < 0.001$). Additionally, confirmatory factor analysis confirms a good fit for its five-factor structure, validating its use in the Chinese cultural context.

In Exp 1, CSAQ-A was collected again after one month to examine the longitudinal screening of SA traits. Furthermore, CSAQ-A similarly exhibited high internal consistency and good test-retest reliability, with Cronbach's α values of 0.96, 0.94, 0.94, and 0.91 at Exp 1, 2a, 2b and 3, and a test-retest reliability of 0.86 at Exp 1.

2.1.5. Data analysis

Correlation and regression analyses were performed using R version 4.2.2 (Team, 2020) to examine associations between SAIPS ratings and SA traits.

Data preprocessing excluded 9 incomplete data due to participant dropout or technical issues, resulting in a final sample of 59 participants for Exp 1. At the one-month follow-up, 5 cases of missing data were excluded, leaving 54 participants for longitudinal analyses. For Exps 2 and 3, only participants who completed all tasks and passed quality control were included, ensuring no missing data. Outlier detection using box plots revealed no values exceeding ± 3 standard deviations across all experiments.

2.1.6. Unsupervised picture classification

To examine clusters of SAIPS pictures, we conducted an unsupervised ML based on five dimensions of ratings for each picture. Unsupervised ML algorithm k-means was conducted for picture classification.

2.1.7. ML algorithms

ML analyses were performed using Python version 3.11.5. ML algorithms were selected to predict SA traits based on SAIPS ratings. The prediction was conducted both for the cross-sectional SA trait and longitudinal SA trait after a month. ML algorithms were implemented using the scikit-learn library in Python (Pedregosa et al., 2011).

For classification, we grouped participants' SA traits into low, medium, and high by thresholds of 81 and 110 (Wang et al., 2024). We included three ensemble learning (combining multiple individual models to improve performance) methods: Random Forest, AdaBoost, and Gradient boosting. For regression, we utilized penalized linear regression techniques, including LASSO, Ridge, and ElasticNet. The results of the best-performing model for each analysis were presented and were further validated through 1000 permutations to ensure robustness and reliability (see Supplemental material S3 for details). Ratings to 118

SAIPS pictures across five dimensions, along with four demographic variables (gender, age, employment, and education) were entered as model inputs, yielding a total of 594 predictors. SA traits served as model outputs, both as continuous and categorical data (e.g., low, medium, and high). We randomly split the data into a train set (80 % of the data) and a test set (20 % of the data). A five-fold cross-validation was conducted for hyperparameter selection. Prediction accuracy and the area under the receiver operator curve (AUC-ROC) were used to measure model performance. Furthermore, the SHapley Additive exPlanations (SHAP) algorithm was used to identify the top influential social anxiety predictors (Arrow et al., 1953). The contribution of different predictor classes (e.g., the contribution of valence ratings of negative pictures) was determined by calculating the weighted average contribution of predictors within each class. See the Supplemental material S3 for further details on model training and testing.

2.2. Results

Participant information was reported in Table 1 for Exp 1, Exp 2a, Exp 2b, and Exp 3.

2.2.1. SAIPS picture classification

Descriptive results of the five-dimensional rating scores of the 118 social pictures are shown in Table 2. These results support the validity of the 118 selected stimulus images, demonstrating that they possess strong evaluative qualities in line with the intended assessment of social anxiety and emotional responses.

As shown in Fig. 2 A, pictures were grouped into 3 clusters based on the elbow point in the scree plot from k-means (see Supplemental material Figure S2 for details of the analysis). The three clusters yielded clear distinctions on the valence dimension and were labeled as negative, neutral, and positive clusters. To examine the differences between 3 picture clusters, a mixed-effect MANOVA was conducted with picture clusters and rating dimensions as factors.

Results showed that the main effects of picture clusters and rating dimensions were significant ($ps < 0.001$). The interaction effect was also significant ($F_{(8460)} = 189.24$, $p < 0.001$, $\eta_p^2 = 0.77$). Posthoc simple effects showed that, for SAR and valence, all three picture clusters showed significant differences (Fig. 2 C, $ps < 0.01$, Bonferroni corrected). While for arousal and involvement, positive pictures scored significantly higher than neutral and negative pictures ($ps < 0.01$, Bonferroni corrected). No significant difference was found in the rating scores of consistency ($ps > 0.05$). See Supplemental material S4 for details of statistical analysis results.

To assess the reliability and relevance of the 118 stimulus images, we performed an item analysis across the five rating dimensions. Specifically, we calculated Cronbach's alpha and item-total correlations for each image type (negative, neutral, positive). The results revealed that Cronbach's alpha values for all three image categories exceeded 0.817, indicating good internal consistency across all dimensions. Additionally, the item-total correlations for each image were all above 0.30 ($ps <= 0.022$), confirming satisfactory item relevance and reliability.

2.2.2. Associations between SAIPS rating and SA traits

Regression analyses were conducted to investigate the relationship between SA traits and picture ratings. As shown in Fig. 2 C, results showed that SA traits were positively associated with SAR (β =0.31, $R^2 = 0.09$, $p < 0.001$), and arousal ratings ($\beta = 0.30$, $R^2 = 0.09$, $p < 0.001$). The moderation analysis did not show a significant moderation effect of picture cluster on the relationships between SA trait and SAR or arousal ratings ($ps > 0.05$; details see Supplemental material S5). Results suggested individuals with greater SA traits yielded greater social anxiety ratings and arousal ratings across all social pictures.

To further validate these findings, a mixed-effect MANOVA analyses were conducted across Exp 1 (as well as Exp 2a, 2b, and 3). The analyses used SA trait group (high/medium/low) as the between-subjects variable and the five-dimensional rating scores (SAR, valence, arousal, involvement, consistency) as the dependent variables.

Results showed that for SAR, the main effects of the SA trait group were significant in studies 1, 2a, 2b, and 3 ($ps < 0.001$), which further confirms the positive correlation between SA trait and SAR.

2.2.3. The prediction of SA traits through ML

2.2.3.1. Cross-sectional SA trait prediction.

As shown in Fig. 3A, Random Forest yielded the best performance among all ML algorithms (see Supplemental material Table S1 for the performance of other models), with an accuracy of 0.67 (chance level 0.33) and an AUC-ROC of 0.80 (chance level 0.5). The accuracy ($p < 0.01$) and AUC-ROC ($p < 0.01$) score achieved significance with permutation tests. Results indicated

Table 1
Demographic information.

	Exp 1 Social Pic 118 Lab (N = 59)	Exp 2a Social Pic 118 Online (N = 121)	Exp 2b Social Pic 161 (N = 126)	Exp 3 Control pic 118 (N = 37)	Overall Pic 397 (N = 343)
Gender					
Female	29 (49.2 %)	59 (48.8 %)	57 (45.2 %)	6 (16.2 %)	151 (44.0 %)
Male	30 (50.8 %)	59 (48.8 %)	67 (53.2 %)	31 (83.8 %)	187 (54.5 %)
Others	0 (0 %)	3 (2.5 %)	2 (1.6 %)	0 (0 %)	5 (1.5 %)
Age					
M (SD)	22.1 (3.07)	28.0 (5.59)	26.9 (6.21)	28.5 (7.06)	26.7 (6.04)
Min, Max	18.0, 33.0	19.0, 45.0	19.0, 45.0	18.0, 43.0	18.0, 45.0
Employment					
Working full-time	0 (0 %)	69 (57.0 %)	45 (35.7 %)	26 (70.3 %)	140 (40.8 %)
Working part-time	2 (3.4 %)	16 (13.2 %)	21 (16.7 %)	2 (5.4 %)	41 (12.0 %)
Unemployed*	1 (1.7 %)	10 (8.3 %)	14 (11.1 %)	1 (2.7 %)	26 (7.6 %)
Homemaker*	0 (0 %)	0 (0 %)	2 (1.6 %)	0 (0 %)	2 (0.6 %)
Student	56 (94.9 %)	25 (20.7 %)	43 (34.1 %)	8 (21.6 %)	132 (38.5 %)
Other	0 (0 %)	1 (0.8 %)	1 (0.8 %)	0 (0 %)	2 (0.6 %)
Education					
High school or lower	7 (11.9 %)	32 (26.4 %)	31 (24.6 %)	9 (24.3 %)	79 (23.0 %)
Undergraduate	31 (52.5 %)	53 (43.8 %)	62 (49.2 %)	17 (45.9 %)	163 (47.5 %)
Postgraduate	16 (27.1 %)	34 (28.1 %)	30 (23.8 %)	9 (24.3 %)	89 (25.9 %)
Phd or above	5 (8.5 %)	2 (1.7 %)	3 (2.4 %)	2 (5.4 %)	12 (3.5 %)
Social Anxiety Trait					
M (SD)	96.4 (24.1)	100 (21.3)	100 (21.2)	91.1 (16.6)	98.4 (21.4)
Min, Max	50, 148	55, 149	44, 148	65, 127	44, 149

Notes: Pic: Pictures; Unemployed: Unemployed and looking for work, Homemaker: A homemaker or stay-at-home parent; M = Mean, SD = Standard Deviation.

Table 2
Descriptive table: *M* (*SD*) for all pictures.

	Exp 1 (Social pics=118)	Exp 2a (Social pics=118)	Exp 2b (Social pics=161)	Exp 3 (Control pics=118)	Overall (All pics=515)
SAR					
M (SD)	6.63 (0.431)	6.54 (0.594)	5.66 (1.59)	4.21 (1.28)	5.75 (1.47)
Min, Max	5.26, 7.95	4.97, 7.85	2.00, 8.91	1.26, 6.85	1.26, 8.91
Valence					
M (SD)	4.46 (1.55)	4.54 (1.23)	6.06 (1.76)	5.32 (0.905)	5.17 (1.58)
Min, Max	2.26, 8.08	2.69, 7.87	2.33, 8.94	2.84, 7.29	2.26, 8.94
Arousal					
M (SD)	6.58 (0.446)	5.62 (0.762)	6.08 (1.20)	4.13 (0.896)	5.64 (1.26)
Min, Max	5.20, 7.65	3.38, 7.94	3.29, 8.44	1.47, 6.37	1.47, 8.44
Involvement					
M (SD)	5.64 (1.12)	6.25 (1.09)	7.18 (0.669)	6.14 (0.884)	6.37 (1.10)
Min, Max	2.25, 7.38	2.15, 8.26	4.70, 8.67	2.78, 7.78	2.15, 8.67
Consistency					
M (SD)	6.84 (0.704)	6.81 (0.885)	7.57 (1.25)	7.06 (0.987)	7.11 (1.05)
Min, Max	4.56, 8.17	3.25, 8.30	1.70, 9.69	2.72, 8.48	1.70, 9.69

Notes. *M* = Mean, *SD* = Standard Deviation.

that the ratings of SAIPS pictures could successfully predict SA traits. As shown in Fig. 3B, SHAP analysis showed greater contributions of SAR in social anxiety prediction, especially SAR of negative pictures, suggesting the social anxiety ratings over negative social scenarios may be the most informative predictors of an individual's SA trait.

Furthermore, we examined the minimum number of pictures to reach a stable prediction. We identified the turning point by smoothing the relationship between the number of pictures and performance score and then applying the "Kneedle" algorithm (Satopaa et al., 2011) on the smoothed curve. Results showed that using 28 SAIPS pictures allows the prediction to reach an elbow point (Fig. 3C), with an R^2 of 0.53 (permutation test $p < 0.01$). The result suggests a subset of SAIPS pictures may be effectively used as a screening tool in the future (see Supplemental material S3 for the details of the condensed version).

2.2.3.2. Longitudinal SA trait prediction. We further investigated the prediction of SA trait scores after one month, focusing on the ability to exclude individuals with high SA trait scores. Among the various ML algorithms evaluated (see Supplemental material Table S2 for the performance of other models), AdaBoost demonstrated the best performance, achieving an accuracy of 0.91 and an AUC-ROC score of 0.83. The accuracy ($p < 0.01$) and AUC-ROC score ($p = 0.02$) were statistically significant, as confirmed by permutation tests. These results suggest the ratings of SAIPS pictures effectively identify individuals with high social anxiety in a one-month follow-up period. The confusion matrix for Adaboost is presented in Fig. 3D. As shown in Fig. 3E, SHAP analysis showed greater contributions of SAR in social anxiety prediction, especially SAR of negative pictures, suggesting the ratings over negative social scenarios may be the most informative predictors of an individual's SA trait. Additionally, we explored the minimum number of SAIPS pictures required to achieve a stable prediction (Fig. 3F). Results showed that using 26 SAIPS pictures allows the prediction to reach an elbow point, with an R^2 of 0.17 (permutation test $p = 0.02$).

3. Experiment 2: online experiments

Experiment 2 aims to further examine the robustness of findings in Experiment 1, namely whether the associations between SAIPS ratings and SA traits can be generalized across cultures, ages, and batches of social pictures. Exp 2a adopted the same 118 social pictures and examined the screening of social anxiety through an online experiment with international participants across cultures. Exp 2b further introduces an extra 161 social pictures to expand the diversity of SAIPS dataset.

3.1. Experiment 2a

3.1.1. Methods

3.1.1.1. Participants and Procedure. A total of 121 individuals were recruited from the Prolific (https://www.prolific.co/) online platform (59 females, age: $M = 28.0$, $SD = 5.59$). Participants showed an even distribution of genders and diverse ethnic backgrounds from 26 countries to enhance the generalizability of our findings. All participants provided their informed consent. Upon completion of the study, participants were compensated with 4.5 pounds for their participation.

The same 118 SAIPS pictures and similar experimental procedures were used as in Experiment 1a. To ensure data quality while limiting experiment duration to approximately 42 minutes, 30 pictures were randomly selected for each online participant from the pool of 118 (or 161 for Exp 2b) SA pictures. Randomization was conducted using Qualtrics, where each participant received a unique set of images with no predetermined patterns or overlaps, minimizing fatigue and ensuring reliable data collection. The same Englisher-version of SAQ-A (Caballo et al., 2012) was collected for each online participant to measure SA trait.

3.1.1.2. Data analysis. Similar data analyses were conducted as in the Exp 1a. Furthermore, we compared the reliability and difference between laboratory (Exp 1) and online (Exp 2a) experimental settings by analyzing the picture-by-picture correlations of ratings. In addition, we also combined the two datasets to examine whether the ML prediction can be generalized across datasets.

3.1.2. Results

Descriptive results of the five-dimensional rating scores for the 118 social pictures are shown in Table 2.

As shown in Fig. 4 A, the correlations of rating scores between laboratory and online experiments were significant in all five dimensions ($r_{[\text{min, max}]} = [0.42, 0.93]$, $ps < 0.001$). The results of Intraclass Coredlation Coefficient (ICC) indicated variability in reliability across dimensions (ICC >= 0.39, $ps < 0.001$; details see Supplemental Table S3) except arousal (ICC = −0.048, $p = 0.698$). Details see Supplemental material S7.

To examine the relationship between SA traits and rating scores, regression analyses were conducted. Results showed that SA traits were positively associated with SAR ($\beta = 0.37$, $R^2 = 0.13$, $p < 0.001$, Fig. 4B) as in Experiment 1. In contrast, other rating dimensions did not yield significant associations with SA traits ($ps > 0.05$; details see Supplemental material S8), not replicating the effect between SA trait and arousal ratings as in Experiment 1. This may be driven by the differences

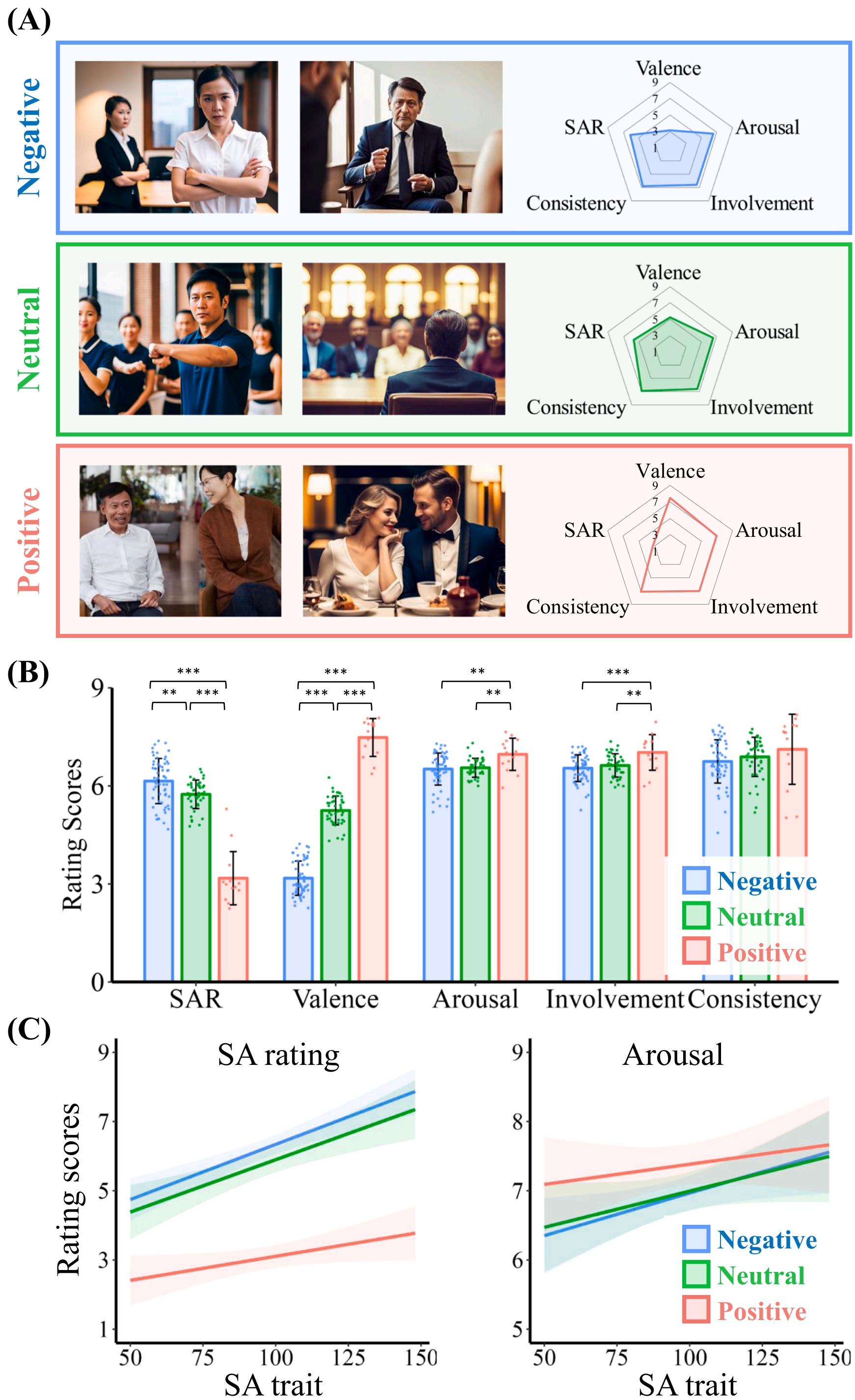

Fig. 2. (A) Instances of SAIPS pictures in the negative, neutral, and positive clusters determined by the K-means algorithm and the corresponding distributions of ratings on the five dimensions for the three picture clusters. (B) Five-dimensional rating scores for three clusters of SAIPS pictures. (C) The relationship between SA trait and SAR, and between SA trait and arousal for three picture clusters. Error bars indicate standard errors. $p < 0.01$, * $p < 0.001$. The shaded area represents the 95 % confidence interval.

in the nature of laboratory and online experiments, as shown by a significant decrease in the ratings of arousal and a significant increase in involvement in the online experiment in comparison to the laboratory experiment ($ps < 0.05$, Bonferroni corrected, details see Supplemental material S7 and Figure S3). The decrease in arousal and the increase in involvement in the online experiment may indicate that subjects were less physiologically involved but more easily mentally immersed in the online rating procedure when being presented with social scenarios.

3.2. *Experiment 2b*

3.2.1. *Methods*

A total of 126 individuals were recruited from the Prolific online platform (57 females, age: $M = 26.9$ $SD = 6.21$).

In Experiment 2b, we introduced another 161 social pictures to examine whether the results can generalize across batches of SAIPS pictures. In the process of constructing the first batch of pictures, we used an unsupervised ML method, K-means clustering, to categorize the

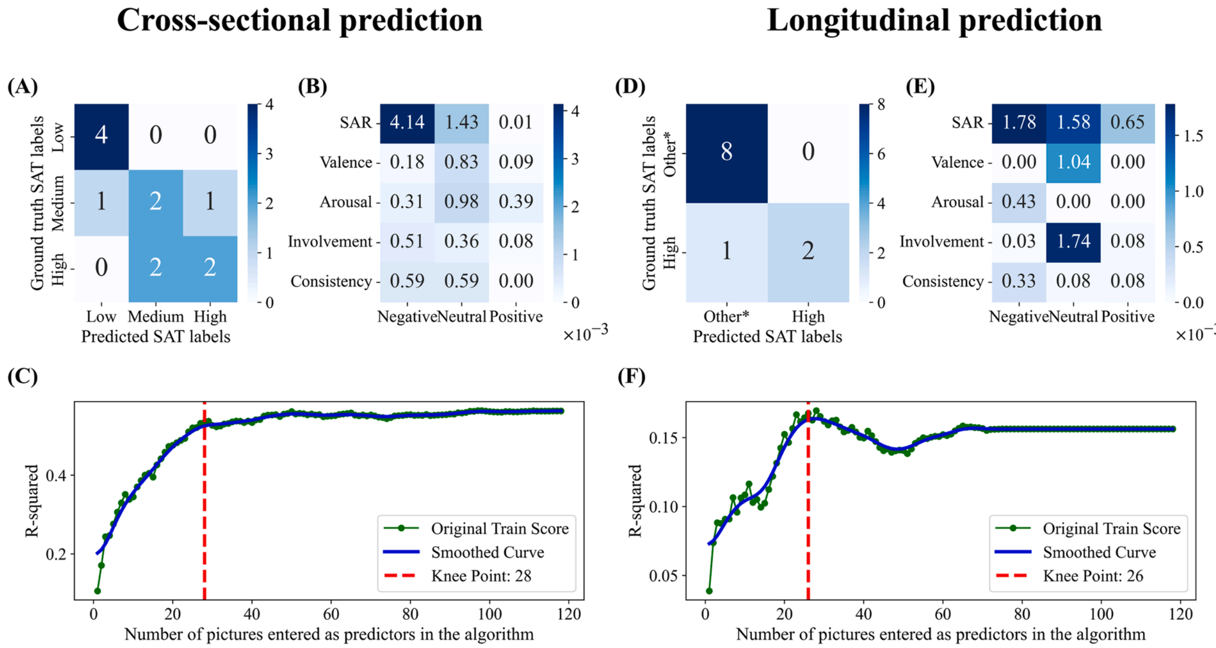

Fig. 3. The cross-sectional prediction of SA traits. (A) The confusion matrix. (B) The average influence of predictors. (C) The change in prediction performance across the number of pictures used as predictors in the ML algorithm. For the longitudinal prediction of SA trait, (D) the confusion matrix, (E) the influence of predictor classes, and (F) the function of model performance of the number of pictures used as predictors. Other* = Low & Medium.

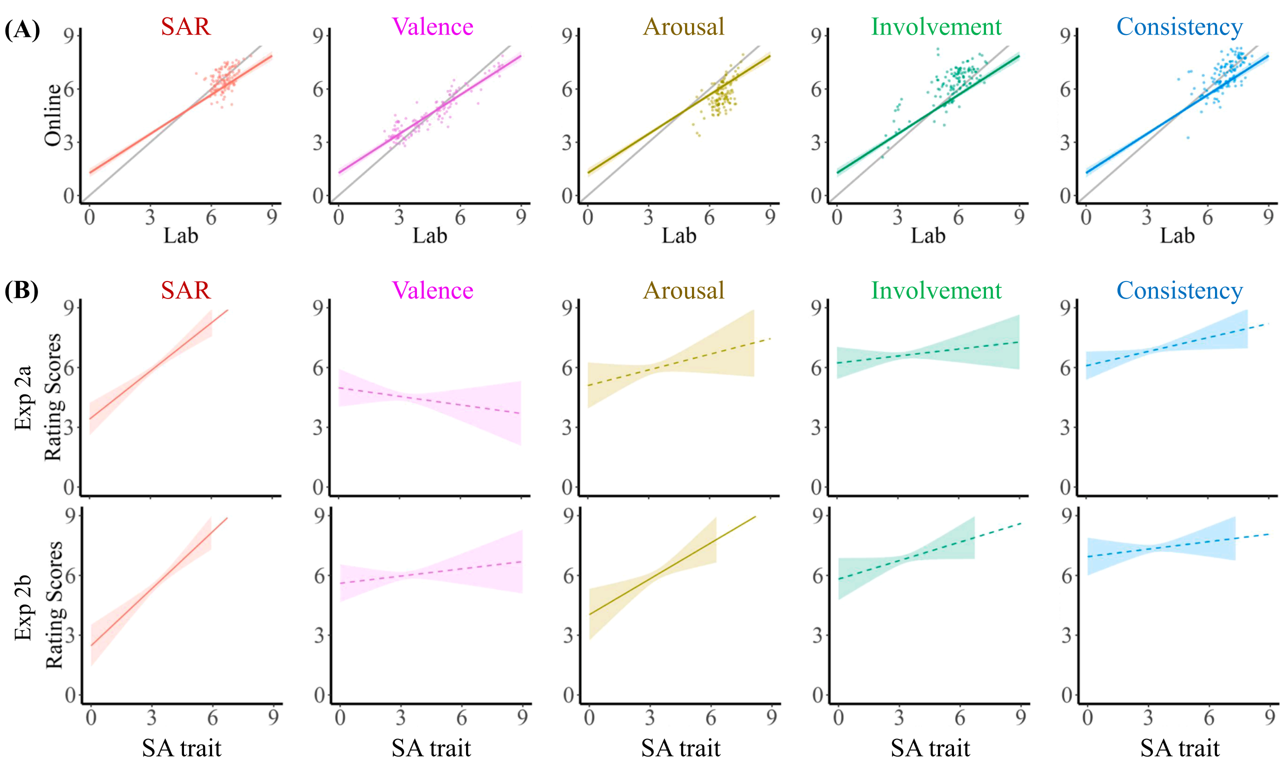

Fig. 4. (A). The relationship of rating scores for 118 social pictures between laboratory and online experiment. The gray diagonal lines represent perfect correspondence as a reference; Lab: Laboratory experiment in Exp 1, Online: Online experiment in Exp 2a; **(B).** The relationship between SA trait and five-dimensional rating scores of 118 social pictures in Exp 2a, and 161 social pictures in Exp 2b. Significant results were presented with solid lines, and non-significant results were presented with dashed lines. The shaded area represents the 95 % confidence interval.

images. Therefore, the number of categories and the distribution of images within each category could only be determined after data collection and the completion of the K-means analysis. Based on the results of the K-means analysis, the first batch of 118 pictures was ultimately divided into three categories. The analysis revealed that the number of negative valence pictures was relatively higher, while the number of positive valence pictures was lower.

To address this imbalance, the newly generated pictures focused on increasing positive valence content, such as joyful gatherings, happy dining with friends, cheerful dates, and enjoyable outdoor activities.

This resulted in a more balanced distribution across the three valence clusters, with a final count of 111 negative, 82 neutral, and 86 positive pictures. Additionally, during the generation of the second batch, imbalances across the three dimensions were corrected to ensure an even distribution at each level. Furthermore, Exp 2b also aimed to balance cultural representation by generating additional pictures, resulting in a relatively equal number of White and Asian faces (125 Asian, 146 White, and 8 mixed-race).

The procedure was similar to Experiment 2a, where five-dimensional rating scores of social pictures were collected from online participants. For each participant, 30 out of 161 pictures were randomly selected for ratings.

3.2.2. Results

Participant information was reported in Table 1. As shown in Fig. 4B, SA traits were positively associated with SAR ($\beta = 0.48$, $R^2 = 0.22$, $p < 0.001$) and arousal ($\beta = 0.29$, $R^2 = 0.08$, $p = 0.004$, Bonferroni corrected). We did not find significant correlations between SA trait and other rating dimensions (*ps* > 0.05, see Supplemental material S8 for detailed reports).

To assess the evaluative equivalence of 118 and 169 stimulus pictures, we conducted a two-factor ANOVA. Results showed a significant interaction between picture category and evaluation dimension ($F_{(4, 448)} = 9.10$, $p < 0.001$). A simple effects analysis revealed that the 169-picture set scored significantly higher on Valence (more positive) compared to the 118-picture set ($t_{(112)} = 4.68$, $p < .001$). No significant differences were found for the other dimensions (*ps* > 0.095). For detailed results, please refer to the Supplemental material S9.

4. Experiment 3: control pictures

Individuals with SAD predominantly experience heightened anxiety in social contexts, particularly in situations that involve interpersonal interaction (Morrison & Heimberg, 2013). Whether engaging in routine conversations or public speaking, they often experience considerable psychological distress and discomfort (Stein & Stein, 2008). Consequently, we seek to investigate whether pictures devoid of social interactions elicit minimal social anxiety and show no significant correlation with individuals' SA traits. Thus, in Experiment 3, we introduced 118 control pictures without social interaction components to serve as a control condition. We hypothesize that with the control pictures, it will not reveal an association between picture ratings and SA trait.

4.1. Methods

A total of 37 individuals were recruited from the Prolific online platform (6 females, age: $M = 28.5$, $SD = 7.06$).

In Experiment 3, 118 control pictures were generated to achieve one-on-one matching of the general settings depicted in the 118 social pictures in Exp 1 (Fig. 5 A), but all human social information was removed. The control pictures were created with the prompt 'Please generate a scene of [specific setting] without people.' The settings of control pictures included environments such as parks, auditoriums, shopping malls, underground stations, business lounges, classrooms, living rooms, gyms, etc. Each social picture has a corresponding control picture, ensuring that the distribution of different settings is consistent between the two types of pictures. Two researchers checked all pictures independently to ensure that the scene matched the intended setting and that there were no distortions or errors.

The experimental procedure was similar to previous experiments, where scores of SA trait and five-dimensional rating scores of 30 out of 118 randomly selected control pictures were collected from online participants.

4.2. Result

4.2.1. Descriptive results and associations with social anxiety

Descriptive statistics for the five-dimensional rating scores were provided in Table 2. SA trait did not yield any significant correlations with rating scores for the control pictures (*ps* > 0.05).

4.2.2. Comparisons for social and control pictures

A mixed-effect MANOVA was conducted with rating dimensions and picture type as factors. The interaction effect was significant ($F_{(4, 936)} = 112.45$, $p < 0.001$, $\eta_p^2 = 0.33$). The main effects of picture type and rating dimensions (*ps* < 0.001) were also significant. As shown in Fig. 5B, posthoc simple effects showed greater rating scores of social pictures than control pictures in SAR, arousal, and involvement, while lower ratings of valence in social than control pictures (*ps* < 0.001, Bonferroni corrected, see Supplemental material S10 for detailed reports).

5. General discussion

Across three experiments, we introduced SAIPS with 279 social pictures and 118 control pictures. We found a robust association between social anxiousness rating on SAIPS social picture ratings and individuals' SA traits, both in laboratory studies (Exp 1a) and online

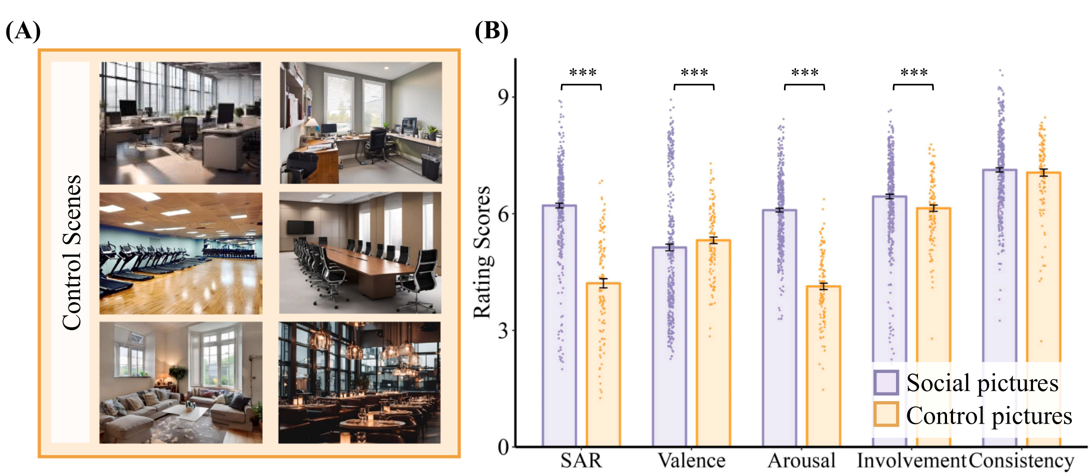

Fig. 5. **(A)** Instances of control pictures (SA pics = 118, N = 180; Control pictures = 118, N = 37); **(B)** The contrast of the five-dimensional rating scores between social and control pictures. Error bars indicate standard errors. * ** $p < 0.001$.

studies (Exp 2a and 2b).

Through ML, we also found that SAIPS picture ratings can reliably predict SA traits both cross-sectional and longitudinally over a month, even with a short version containing a subset of 26 or 28 pictures.

The reliable association between SAIPS social anxiousness rating and SA traits was not surprising, but it serves as promising evidence to support the Research Domain Criteria (RDoC) framework (Cuthbert, 2014), extending measurements of mental disorders from self-report questionnaires to behavioral indices. Previous studies encountered difficulties finding coherence across data modalities targeting one construct. For example, Peng et al. (2023) found a lack of latent structure across units of analysis targeting depression and anxiety (for similar findings, see Eisenberg et al. 2019, and (Frey et al., 2017)). Specifically, a few studies used correlational approaches and indicated a lack of coherence between behavioral and self-report measures for self-control (Echiverri-Cohen et al., 2021; Saunders et al., 2018), impulsivity (Cyders & Coskunpinar, 2011), distress tolerance (McHugh et al., 2011), and cognitive empathy (Murphy & Lilienfeld, 2019); see (Dang et al., 2020) for a review. Thus, to find effective alternative measurements to replace self-report questionnaires, we may need to consider both the construct validity and the face validity. Here, SAIPS pictures may hit the sweet spot by bridging traditional self-report judgments in questionnaires and real-life social scenarios. Social scenario images may capture immediate emotional responses, providing a more accurate assessment of social anxiety and arousal. The picture method also reduces cultural bias by using universally relevant scenarios. Additionally, SAIPS supports large-scale, remote applications, making it ideal for clinical screening and longitudinal tracking, and therefore improving objectivity, sensitivity, and practicality compared to traditional questionnaires.

Furthermore, the interaction effects between rating dimensions and picture type observed revealed specific characteristics of social processing among individuals with social anxiety (Chen et al., 2020; Rozen & Aderka, 2023). Negative pictures elicited stronger anxiety responses, aligning with the theory of threat-related attentional bias (Bar-Haim et al., 2007); (Heeren et al., 2015), and cognitive distortions of threat overestimation and self-focused attention (Clark et al., 2003). In contrast, positive pictures elicited higher ratings of valence, arousal, and involvement, indicating that individuals with social anxiety remain sensitive to positive social scenarios, linking to a fear of positive evaluation (Fredrick & Luebbe, 2020). These biases underscore the complexity of emotional processing in social anxiety, where sensitivity to both positive and negative stimuli coexists, highlighting potential intervention targets such as attention bias modification to balance these responses.

In addition, social pictures were rated lower in valence than control pictures, suggesting they evoke more negative emotions (Reichenberger et al., 2019). This aligns with the negativity bias in social anxiety, where individuals focus on negative aspects of social contexts (Hirsch et al., 2006; Morrison & Heimberg, 2013). The observed negativity bias may explain the lower valence ratings of social pictures compared to non-social controls, reflecting the heightened vigilance and negative interpretation of social cues in individuals with social anxiety.

Together, these findings offer valuable insights into the emotional processing patterns underlying social anxiety and their implications for intervention strategies. For example, incorporating strategies such as expectancy violation, deepened extinction, and variability into intervention therapies may effectively address the negativity bias identified in our study. These strategies could be integrated into established therapies, including exposure therapy (Craske et al., 2014) and cognitive behavioral therapy (Kindred et al., 2022). Such an approach has the potential to foster more adaptive emotional processing and enhance long-term therapeutic outcomes for individuals with social anxiety.

The current study also bears a few limitations that can be addressed in the future. First, the random selection of stimuli may have introduced inter-participant variability. Each participant rated a unique subset of pictures, which could slightly reduce measurement reliability and obscure subtle effects due to variability in stimuli characteristics. Future research could address this by employing a partially randomized design, where some core stimuli are rated by all participants alongside additional randomized stimuli, to balance variability and comparability. Second, pictures cannot reach ecological validity as much as VR or real-life scenarios (Zhang et al., 2024). Future studies can further investigate the possibility of social anxiety screening through VR tasks, where the SA traits of participants may be revealed through interactions with virtual human agents in different scenarios. Third, future investigations could look into the possibility of using wearable devices to measure physiological data (e.g., heart rate and skin conductance) during the perception of SAIPS pictures, which may provide more direct arousal indices for social anxiety screening. Fourth, it remains unknown whether SAIPS ratings would also suffer from memory and repetition effects and suffer in repeated longitudinal studies. Finally, the current study focused exclusively on adults and non-clinical individuals, limiting its generalizability to broader populations. Future research should examine the reliability and applicability of SAIPS tool in younger populations and evaluate its safety and effectiveness in clinical settings (Huckvale et al., 2019).

Together, we proposed SAIPS as a promising screening tool for social anxiety. SAIPS may contribute to the field of mental health from the following perspectives. First, this study developed SAIPS pictures database, overcoming limitations in previous research where experimental materials lacked specificity and comparability, thus promoting more standardized and replicable social anxiety research. Through SAIPS, researchers can more effectively capture and analyze SA traits, eliminating the influence of material differences on related findings in the field, and thereby enhancing research precision and comparability.

Second, with just 26 or 28 images, SAIPS can reliably and accurately reflect individual SA traits, producing efficient and dependable predictive results in both cross-sectional and longitudinal data. This not only enhances SAIPS's utility as a research tool, providing a reliable and efficient method for early identification of social anxiety and advancing the development of mental health screening tools, but also highlights its value in clinical screening and early diagnosis, offering new directions for the diagnosis and treatment of social anxiety and related psychological disorders.

Third, SAIPS not only fills the gap in experimental materials for social anxiety research but also serves as a critical reference tool for future screening, diagnosis, and treatment of social anxiety. It holds the potential to become a clinical screening and early diagnostic tool. SAIPS will be available under an open-access license, providing multidimensional, standardized experimental materials for future social anxiety research, supporting quantitative, replicable, and comparable studies, and facilitating the development of an objective evaluation and diagnostic system for social anxiety.

Finally, SAIPS marks the possibility of transforming mental health constructs from questionnaires to pictorial database systems through generative AI models. While maintaining the theoretical constructs embedded in questionnaires, the current approach transforms questionnaires into multi-modal stimuli with greater biological validity and thus partially overcomes the limitations of subjectivity and memory biases usually associated with questionnaire measurements. Tools such as SAIPS may be widely applied in repeated measurements of personal traits and mental health characteristics, promoting more easily accessible and reliable longitudinal measurements.

CRediT authorship contribution statement

Qianqian Ju: Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Zhijian Xu:** Writing – review & editing, Resources, Methodology, Data curation. **Zile Chen:** Writing – review & editing, Resources, Methodology, Data curation. **Jiayi Fan:** Writing – review &

editing, Writing – original draft, Methodology, Formal analysis. **Han Zhang:** Writing – review & editing, Resources, Methodology, Data curation. **Yujia Peng:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no competing interests with the current study.

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Additional Information

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data and code necessary for replicating the analyses are available at https://osf.io/yn9kc/.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.janxdis.2024.102955.

Data availability

Data will be made available on request.

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