STEMorph: A Set of Morphed Emotional Face Stimuli from Angry to Happy Derived from *NimStim*

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Abstract

Emotion recognition through facial expressions is crucial for interpreting social cues. However, it is often influenced by biases, i.e, systematic recognition advantages for particular emotions. Nevertheless, these biases are inconsistently reported across studies, likely due to methodological variations which underline the necessity for a standardized approach. Traditional face morphing methods can create unnatural-looking stimuli, and may confound the interpretation of emotions. To address this issue, we here introduce *STEMorph*, a validated stimulus set based on the NimStim set. We employed neutral-anchored morphing and neural-network-generated masks to ensure the natural appearance and integrity of the depicted emotions. We validated our stimulus set by having participants rate each face on a 9-point scale ranging from angry to happy, assessing the perceived emotional intensity. *STEMorph's* validity was confirmed through linear regression analysis, showing a strong correlation between subjective ratings and targeted emotional states. Moreover, aligning with previous research highlighting gender as a key factor in emotion recognition, *STEMorph* also exhibits variations in ratings across gender subgroups. *STEMorph's* reliability was confirmed through a two-week follow-up rating session with a subgroup of the same participants. By introducing a controlled, validated, and ecologically valid stimulus set of emotional faces, *STEMorph* paves the way for further investigations into facial emotion recognition, deepening our understanding of this vital aspect of human interaction.

Keywords: *STEMorph*, Stimulus Set, Facial Emotional Expressions, Morphed Stimuli, *NimStim*

Introduction

Emotion recognition is a fundamental aspect of human social interaction, allowing individuals to interpret and respond appropriately to the emotional states of others. Facial expressions serve as a primary modality for conveying emotions, providing valuable cues about an individual's internal states (1). However, despite its significance, the process of emotion recognition is not devoid of biases. These biases manifest as systematic recognition advantages for particular emotions and have significant implications for both clinical and non-clinical populations (2).

Recognition biases can vary across different conditions. Individuals with major depressive disorder (MDD) tend to interpret neutral or ambiguous faces as sad or threatening, reflecting a negativity bias. This aligns with findings that people with MDD are more attuned to negative emotions and less responsive to positive ones, which impairs their ability to interpret emotional cues (3, 4). Such biases may reinforce mood-congruent cognitive distortions, contributing to the maintenance and exacerbation of depressive symptoms (5, 6). Similarly, individuals with generalized anxiety disorder (GAD) and social anxiety disorder (SAD) exhibit hypervigilance toward negative emotional cues, such as anger or fear, which can lead to misinterpretations of facial expressions and reinforce maladaptive emotional responses (7, 8). Therefore, these biases can significantly impact social interactions and clinical outcomes; emphasizing the importance of their precise measurement for both research and clinical applications.

Studies often report inconsistent results regarding the direction and magnitude of emotional recognition biases (9). For instance, one study found that healthy individuals did not demonstrate a bias toward happiness or sadness when presented with neutral facial expressions (10). While another study showed that healthy participants tended to perceive neutral faces as expressing happiness, whereas depressed individuals interpreted them as neutral (8). It is uncertain whether these mixed findings reflect genuine individual differences in emotion perception or are due to methodological variations between the studies (11). Particularly, the quality and ecological validity of facial stimuli can

significantly impact participants' responses. While standardized photographic stimuli are commonly used for their control over visual properties, they may not fully capture the complexities of real-world facial expressions, which can lead to discrepancies in findings. Research indicates that more naturalistic stimuli, such as dynamic or spontaneous facial expressions, enhance ecological validity but introduce variability that complicates experimental control (12, 13). Consequently, A key challenge lies in creating stimuli that maintain natural appearance while allowing precise control over emotional expressions (12, 13).

One widely used approach to generating a continuum of emotions is through face morphing techniques. Face morphing is an image processing technique employed to achieve transformation from one face to another and facilitates a gradual transition between two facial images. By morphing facial features between two extreme emotional expressions, researchers generate a spectrum of face images with ambiguous emotional expressions for participants to interpret (14, 15). However, traditional face morphing presents challenges, particularly concerning the formation of unrealistic and unnatural facial stimuli (15) which may confound interpretations and obscure real emotion recognition processes.

To maintain naturalism, proper masking of the face images (extracting the face area while removing the background) is required, as morphing introduces artifacts in non-face regions. Using no mask (full head) or simple oval/square masks which are employed by many studies (12) may cause distortions that risk emotional content loss, since various facial features hold different degrees of significance depending on the type of expression (16, 17). For instance, the mouth region is particularly salient for recognizing happiness, while the eyes are more critical for identifying fear or sadness (18). These regional differences can lead to biases in emotion perception, as individuals may focus on different facial features based on cultural or individual preferences (17). These underscore the necessity for stimuli preserving anatomical fidelity through methods like neutral-anchored morphing (11) and standardized masking. However, there are no existing publicly available stimulus

set without these methodological confounds (12, 15, 19). While sets like the Karolinska Directed Emotional Faces (KDEF) (20) and the Pictures of Facial Affect (POFA) (21) provide valuable resources, they often rely on basic morphing techniques that can produce artifacts, particularly around facial features crucial for emotion recognition such as the eyes and mouth. Furthermore, many existing sets use simple geometric masks (oval or rectangular) that can create artificial boundaries and reduce ecological validity (12, 15). To address this gap, we developed and validated a new stimulus set utilizing neutral-anchored morphing alongside neural-network-generated masks, to optimize naturalism and coherence.

We derived the stimuli from the *NimStim set of facial expressions* (22) which is a comprehensive collection of facial images portraying a spectrum of emotions including happy, angry, and neutral expressions. The selection of anger and happiness as the target emotions for this study was based on their distinct valence and arousal profiles, which make them suitable for exploring biases in emotion recognition. Additionally, these emotions are commonly used in emotion research (2, 11), facilitating comparisons with existing literature. Investigating the transition between these emotions allows us to examine biases in emotional perception across a clear positive-negative emotional gradient, which is particularly relevant for studies on mood disorders and social cognition (2). We adopt a nuanced approach to morphing emotional faces by generating distinct naturalistic face masks for each image using neural networks. Furthermore, we utilize the neutral facial expression as a central anchor point to enhance the naturalistic quality of the stimuli. We then evaluate the validity and reliability of *STEMorph* by asking a group of participants to provide ratings of the emotional content of these stimuli.

Method

Participants

A total of 50 participants (age range: 18–26 years; mean age: 21.5; 22 females) were recruited for the validity testing. Recruitment took place between March 1, 2023, and December 28, 2024. All

participants were medical students from either Tehran University of Medical Sciences (TUMS) or Shahid Beheshti University of Medical Sciences (SBUMS). All participants reported having normal or corrected-to-normal vision and no history of diagnosed neurological or psychiatric disorders. Written informed consent was obtained from each participant prior to participation, and all were compensated financially for their time. The study received ethical approval from the Ethics Committee of Shahid Beheshti University of Medical Sciences.

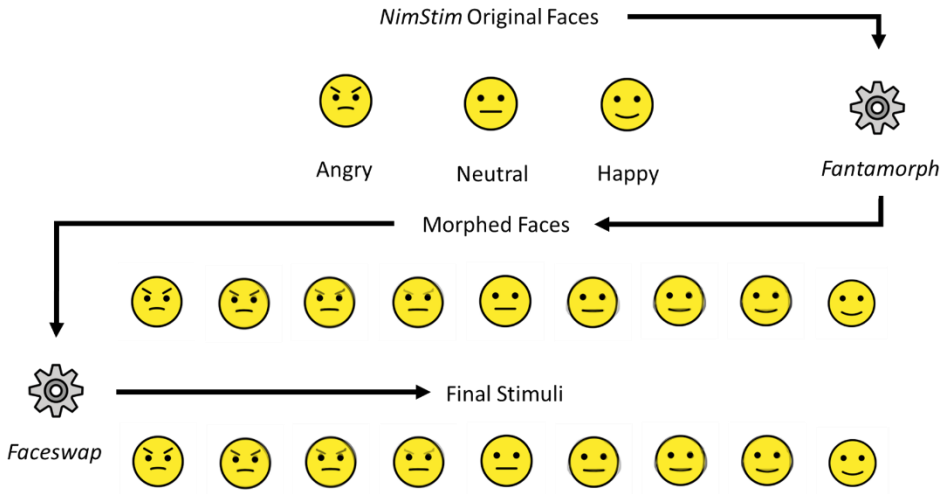
Experiment design & Face Generation

We used face morphing to produce a linear transition of emotions from anger to happiness using neutral expression as an intermediary point. The stimuli were derived from the *NimStim set of facial expressions (22)*. Each emotional expression has an open-mouth and closed-mouth variation in *NimStim*, from which we selected closed-mouth variations. *Abrosoft Fantamorph (23)* software was used for morphing, involving nine steps to transition from the angry face to neutrality and subsequently to the happy face. We used the original facial expressions of anger, happiness, and neutral as reference points and generated three intermediate emotional states between each original face.

We selected 22 individuals (11 males and 11 females) from *NimStim*, prioritizing those whose facial expressions facilitated smooth and natural morphing while avoiding individuals with extreme facial expressions (highly exaggerated or intense displays of emotions). The final set is composed of 198 distinct faces, representing 9 different emotional steps for each of the 22 individuals (Figure 1).

Figure 1

Example Stimuli from the Set.



Note. Top row illustrates the two ends of the spectrum (happy and angry) along with the middle step (neutral). Middle row shows the intermediary morphing stages without masking. Bottom row shows the final outcome with corresponding neural-network-generated masks applied to each morphing step.

To address artifacts introduced in the ears, hair, and other non-landmark regions of the face during conventional face morphing, we generated distinct naturalistic face masks for each image using the *FaceSwap (24)* software, which utilizes the *Bisenet-FP (25)* neural network. *BiSeNet-FP* is a modified lightweight neural network designed for face parsing. The model was set to not include hair or ears and extract only the face region. Manual editing was performed to correct for any artifacts arising from stray hair (e.g., a strand of hair overlapping the face resulted in a split in the face) or other extraneous features.

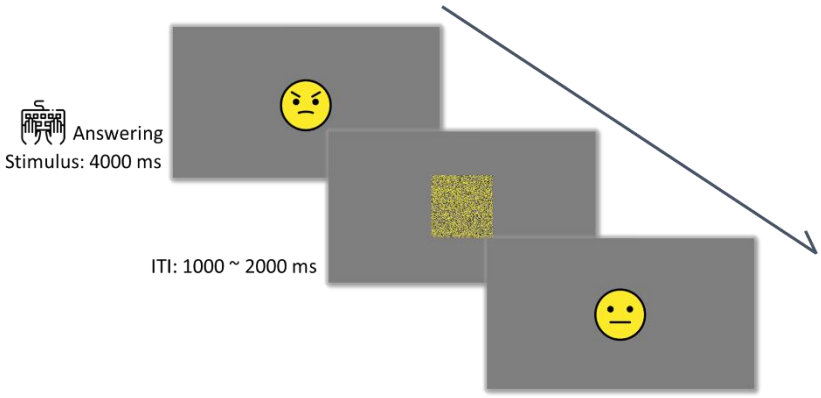
Experimental Setup

Participants were asked to rate the emotional state of each presented stimulus on a 9-point scale from angry to happy. The task was developed and implemented using *Psychtoolbox (26)* within *MATLAB R2022a* (Figure 2). Participants were comfortably seated in a dimly lit room facing a laptop

monitor. The resolution of monitor screen was 1920 × 1080 and it was positioned ~54 cm from the participant. Participants were instructed to freely observe the images without fixation requirements.

Figure 2

Schematic presentation of the experimental design.



Note. Stimuli appeared at the center of the screen, and participants rated the emotional intensity of each face within a 4000 ms viewing window without fixation restrictions. Each stimulus was followed by a randomized inter-trial interval (ITI) of 1000 to 2000 ms, during which a noise mask was displayed.

The task started with pressing a key, after which participants were asked to rate the emotional state of each presented face based on a 9-point scale where 1 indicated the angriest emotional state and 9 indicated the happiest emotional state. The exact instructions were: 'Please rate the emotional state of each face on a scale from 1 to 9, where 1 represents the angriest expression and 9 represents the happiest expression.' To control for motor and numerical biases, the scale was reversed for half of the participants. For these individuals, the instructions were adjusted accordingly, and their responses were rescaled during analysis to align with the original scale (1 = angry, 9 = happy). Each participant had a 4-second window to provide their rating; in the absence of a response within this timeframe, the task automatically proceeded to the subsequent face.

Each of the 198 stimuli was presented twice in a randomized order, resulting in a total of 396 trials per participant, interspersed by two 2-minute breaks. Following each trial, a randomized inter-trial interval (ITI) of 1000 to 2000 ms ensued, during which a noise mask was displayed at the center

of the screen to prevent from interference between trials and minimize priming effects (27, 28). To generate the noise mask the stimulus presented in the previous trial was scrambled into 4-pixel squares.

Reliability Assessment

To assess reliability, the same behavioral task was readministered to a subgroup of 23 participants two weeks following their initial participation. This subgroup consisted of participants who agreed to return for retesting (age range: 18-26, mean age: 22, 5 females).

Data Analysis

Validity

To investigate the relationship between morph levels and subjective ratings while accounting for gender effects, we conducted an Ordinary Least Squares (OLS) linear regression analysis using *statsmodels (29)*. The model included morph step (1-9), face gender (male/female), participant gender (male/female), and all two-way interactions as predictors of participants' emotional ratings as below:

Equation (1):

$$\boldsymbol{Participans' \ Rating} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1\boldsymbol{MS} + \boldsymbol{\beta}_2\boldsymbol{FG} + \boldsymbol{\beta}_3\boldsymbol{PG} + \boldsymbol{\beta}_4(\boldsymbol{MS} \times \boldsymbol{FG}) + \boldsymbol{\beta}_5(\boldsymbol{MS} \times \boldsymbol{PG}) + \boldsymbol{\beta}_6(\boldsymbol{FG} \times \boldsymbol{PG}) + \boldsymbol{\varepsilon}$$

where MS corresponds to Morph Step (1-9), FG to Face Gender (0=female, 1=male), PG to Participant Gender (0=female, 1=male), $\boldsymbol{\beta}$ to coefficients of each regressor, and ε to error term. Given that this is an effort to validate a stimulus set, all collected participants were included in analyses, with no outlier removal being performed. We then calculated partial residuals for morph steps by removing variance explained by gender-related terms to isolate the morph-rating relationship.

To quantify evidence strength against null models, we computed Bayes Factors using the *BayesFactor* (30) R package. Statistical power (1- β error) was determined through *G*Power* (31) with $\alpha = 0.05$ relative to a non-correlation model ($\rho\ H_0 = 0$). To visualize partial regression plots we generated violin plots using matplotlib (32) and seaborn (33).

Gender Subgroup Analysis

To examine gender-specific effects on emotion perception, we extended our primary regression framework (Equation 1) through partial regression analysis of participant gender and face gender subgroups. We computed condition-specific partial residuals from the full model (Equation 1) to isolate morph-rating relationships within gender subgroups.

For participant gender subgroups, we calculated partial residuals by retaining morph step, participant gender (Female/Male), and their interaction (Morph Step × Participant Gender), while regressing out variance associated with face gender effects (Face Gender + Morph Step × Face Gender + Face Gender × Participant Gender) (Equation 2). Additionally, in face gender subgroup analysis, morph step, face gender (Female/Male), and their interaction (Morph Step × Face Gender) were preserved while variance attributable to participant gender effects (Participant Gender + Morph Step × Participant Gender + Face Gender × Participant Gender) were removed (Equation 3). This approach enabled examination of gender-specific emotion perception while controlling for cross-gender interactions.

Equation (2)

$$\boldsymbol{Participant\ Gender\ Partial\ \ Rating = Particiapans'\ Rating - (\beta_2 FG\ +\ \beta_4(MS \times FG)\ +\ \beta_6(FG \times PG))}$$

Equation (3)

$$\boldsymbol{Face\ Gender\ Partial\ Rating = Particiapans'\ Rating - (\beta_3 PG\ +\ \beta_5(MS \times PG) +\ \beta_6(FG \times PG))}$$

Where MS corresponds to Morph Step (1-9), FG to Face Gender (0=female, 1=male), PG to Participant Gender (0=female, 1=male), $\boldsymbol{\beta}$ *to coefficients of each regressor and ε to error term.*

Reliability

To investigate reliability, we analyzed data from participants who engaged in the retesting (n = 23) and compared it with their validity data. We exactly matched trials from the two tasks based on

the presented face and performed OLS linear regression between participants' ratings in the validity task and the retest conducted two weeks later as below:

Equation (4):

$$\boldsymbol{Particiapans' \ Retest \ Rating} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{VR} + \boldsymbol{\varepsilon}$$

where VR corresponds to Validity Ratings (1-9), $\boldsymbol{\beta}$ to coefficient of VR, and ε to error term. We then calculated the Bayes Factor and Statistical power using the methods previously described.

Results

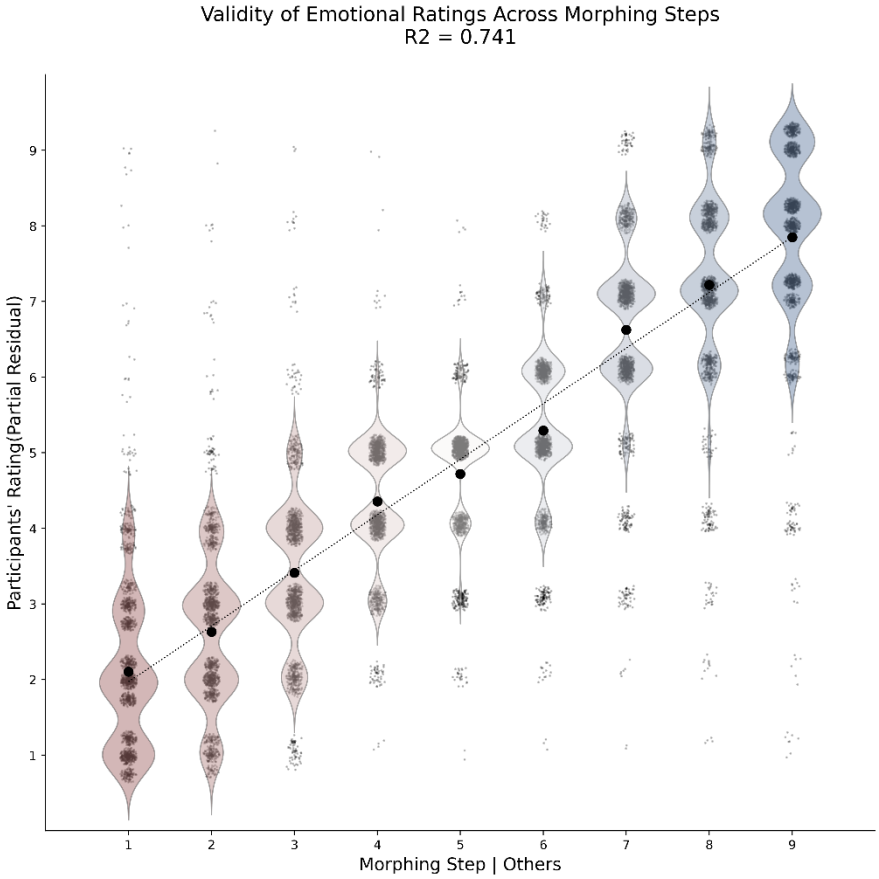
The aim of this study was to develop and validate a new stimulus set for emotion recognition utilizing neutral-anchored face morphing and neural-network-generated masks to optimize naturalism and coherence. A total of 50 participants were recruited to rate the emotional content of the face stimuli on a 9-point scale ranging from angry to happy with a subset of 23 participants returning for a reliability assessment two weeks later.

Validity

We employed linear regression to examine the emotional ratings provided by participants (mean = 4.85, SD = 2.14) against the emotional morph level of the stimulus set, while accounting for face gender, participant gender, and their interactions (Table 1). The model revealed a strong positive association between morph step and emotional ratings, with a coefficient estimate of 0.735 (95% CI [0.724, 0.746], $p < 0.001$). The model explained a substantial proportion of variance in ratings ($R^2 = 0.741$, $p < 0.001$; Figure 3). The Bayes factor comparing the model to the null hypothesis ($R^2 = 0$) approached infinity, indicating strong evidence in favor of the model. Furthermore, the statistical power (1 − β error) relative to a non-correlation model ($\rho \ H_0 = 0$) was 0.999, demonstrating robust sensitivity to detect the observed effect.

Figure 3

Validity of emotional ratings across morphing steps.



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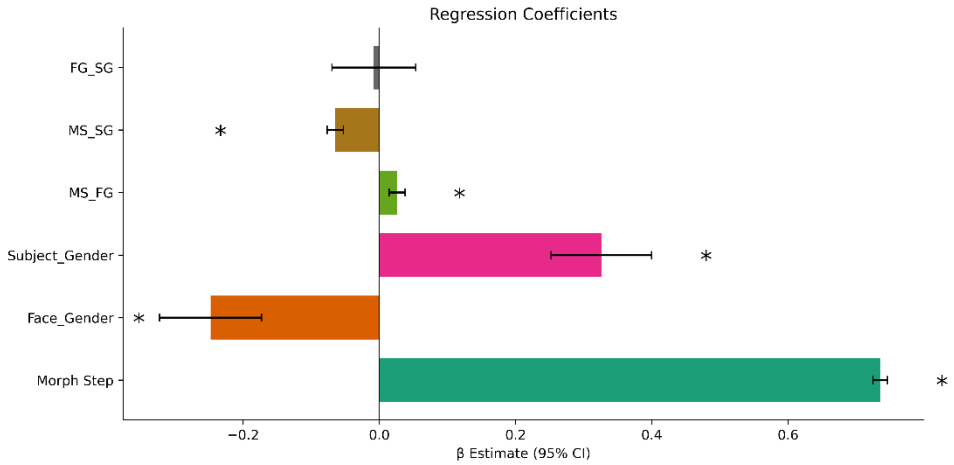
Note. Morphing steps range from angry (1) to happy (9) on the x-axis. The y-axis presents participants' emotional ratings as partial residuals after removing variance explained by gender-related terms (face gender, participant gender, and interactions). Violin plots show kernel density estimates of rating distributions at each morph step. Extreme outliers (±2SD from morph-level means) were excluded only for visualization clarity purposes (all data retained in statistical models). Small grey dots depict raw residuals, large black dots indicate mean ratings, and the dashed line shows the regression slope. The equation reflecting the full mode is: Participants' Rating = 0.735 × MS + -0.248 × FG + 0.326 × PG + 0.026 × (MS×FG) + -0.065 × (MS×PG) + -0.008 × (FG×PG) + 1.236 where MS corresponds to Morph Step (1-9), FG to Face Gender (0=female, 1=male) and PG to Participant Gender (0=female, 1=male). Colors correspond to morph steps.

Figure 4

Regression coefficients for the model.



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Note. Beta estimates (95% CIs) from the OLS regression model predicting emotional ratings. Predictors include Morph Step (MS; 1–9), Face Gender (FG; 0 = female, 1 = male), Participant Gender (PG; 0 = female, 1 = male), and their two-way interactions. Asterisks denote terms significant at α = 0.05.

Table 1

Ordinary Least Squares Regression Results.

Predictor	*β*	*SE*	*t*	*P > |t|*	*[0.025*	*0.975]*
const	1.236	0.032	38.715	**<0.001**	1.174	1.299
Morph Step	0.735	0.005	134.882	**<0.001**	0.724	0.746
Face_Gender	-0.248	0.038	-6.485	**<0.001**	-0.323	-0.173
Participant_Gender	0.326	0.038	8.665	**<0.001**	0.252	0.400
MS_FG	0.026	0.006	4.324	**<0.001**	0.014	0.038
MS_PG	-0.065	0.006	-10.669	**<0.001**	-0.077	-0.053
FG_PG	-0.008	0.031	-0.252	0.801	-0.069	0.054

Note. OLS regression results from the full interactive model (Equation 1). The model explains 74.1% of variance in emotional ratings (R^2 = 0.741, N = 19,596 observations). Morph Step (MS) represents emotion

intensity progression (1: angry to 9: happy). Face/Participant Gender coded 0 = Female, 1 = Male. Significant terms (α = 0.05) marked with asterisks. The non-significant Face × Participant Gender interaction (p = 0.801) indicates additive rather than multiplicative gender effects.

Gender Subgroup Validity Analysis

To assess the robustness of validity across gender dimensions, we included gender of face stimuli and gender of participant in our model as described above (Equation 1). Significant effects were observed for face gender ($\beta = -0.248$, $p < 0.001$), participant gender ($\beta = 0.326$, $p < 0.001$), and the interactions between morph step and face gender ($\beta = 0.026$, $p < 0.001$) as well as morph step and participant gender ($\beta = -0.065$, $p < 0.001$; see Figure 4). The interaction between face gender and participant gender was not significant ($\beta = -0.008$, $p = 0.801$). In other words, female faces received higher ratings than male faces, whereas male participants provided higher ratings than females.

To evaluate the validity of participants' ratings in gender subgroups, we analyzed partial residual for each subgroup. Strong predictive validity across subgroups were observed. Morph step slopes for face gender subgroups (Figure 5a) were nearly identical (R^2 female faces: 0.759; R^2 male faces: 0.759), with slopes and interactions as below:

Female Faces: 1.24 + 0.74 × Morph Step; Male Faces: 0.99 + 0.76 × Morph Step

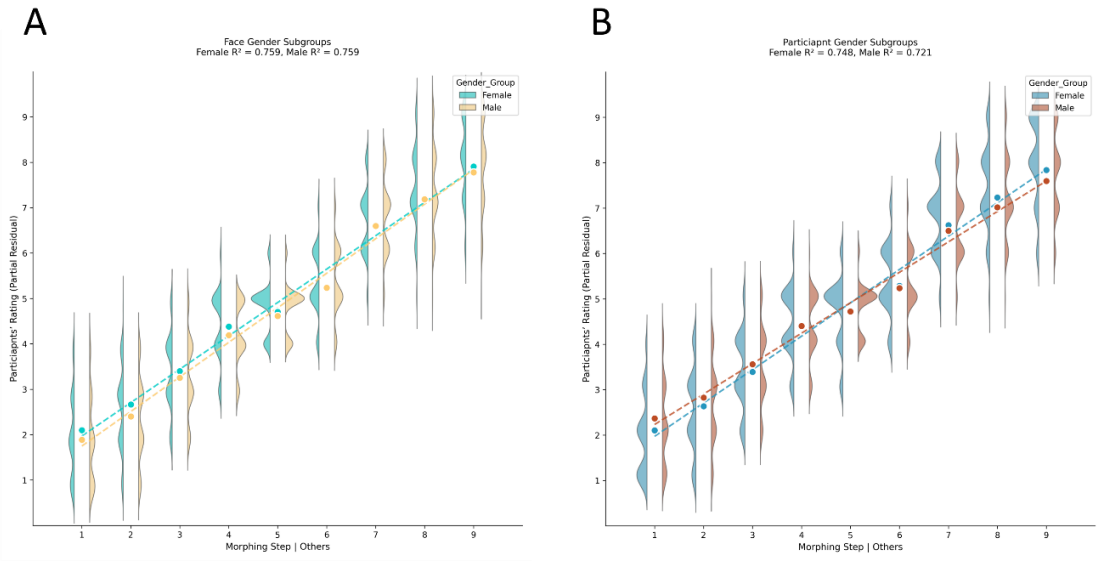
Participant gender subgroups exhibited greater divergence where female raters showed steeper slopes ($R^2 = 0.748$) than male raters ($R^2 = 0.721$, Figure 5b), suggesting gender-related differences in emotional rating:

Female Participants: 1.24 + 0.74 × Morph Step; Male Participants: 1.56 + 0.67 × Morph Step

The strong R^2 of the partial regression analysis across subgroups confirm robust validity across gender dimensions while highlighting nuanced differences in how participant gender relates to emotion perception accuracy.

Figure 5

Gender-based subgroup analysis of the validity data.



Note. A) Face gender subgroups: Female faces (blue) and male faces (orange) show comparable morph-rating slopes derived from partial regression analysis. B) Participant gender subgroups: Female participants (blue) demonstrate steeper slope than male participants (orange) in partial residuals. Violin plots display distributions of gender-specific partial residuals at each morph step (1: angry to 9: happy), with dashed lines showing ordinary least squares fits to residualized data. Large markers indicate mean ratings per morph step. Extreme outliers (±2SD from morph-level means) were excluded only for visualization clarity purposes (all data retained in statistical models). Trendline equations reflect slope estimates from residualized relationships, with shared R^2 value from the full interactive model.

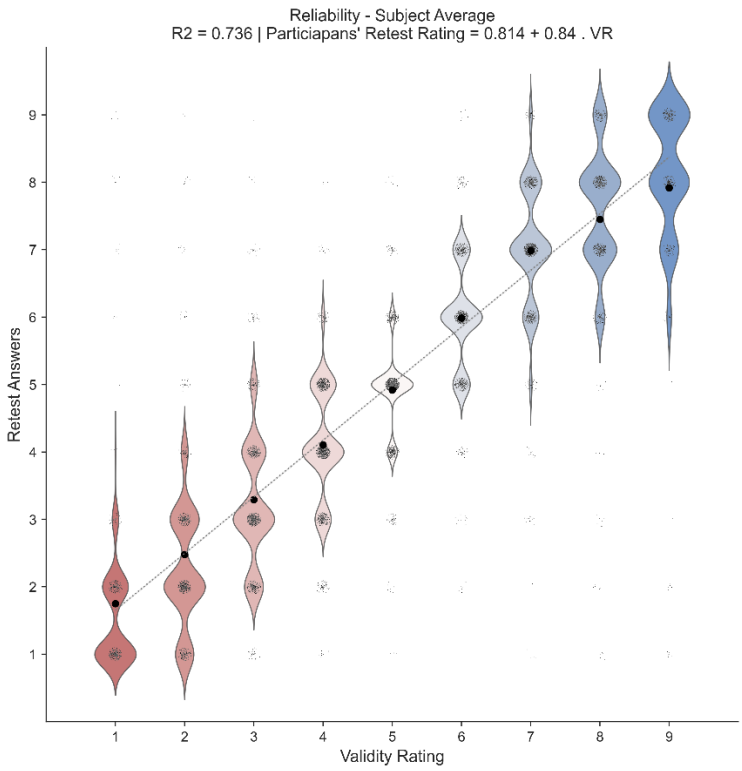
Reliability

To evaluate reliability, we examined the relationship between the validity and the retest ratings using a linear regression model. This model had a coefficient of determination (R^2) of 0.736 (p-value < 0.001) (Figure 6) and the coefficient estimate for the validity answers was 0.84, with an intercept of 0.814. The high R^2 value indicates strong test-retest reliability, suggesting minimal variability in interpretations of the stimulus set across multiple exposures. The Bayes factor, comparing the calculated regression to the null hypothesis ($R^2 = 0$), was infinite, showing strong evidence in favor

of H1. Moreover, the calculated statistical power (1 – β error) in comparison with the non-correlation model (Correlation ρ H0 = 0) was 0.999, demonstrating robust sensitivity to detect the observed consistency in participants' ratings.

Figure 6

Reliability of participants' ratings between the initial test and the retest session.



Note. The x-axis denotes the ratings from the first task (validity ratings), and the y-axis corresponds to ratings from the retest. The violin plots depict the distribution and probability density of ratings at each step, with individual trials displayed by small grey dots. The means of the retest ratings are marked with black dots, and the regression line is presented by a dashed line. The regression outcome and R^2 values are displayed in the figure. The colors are used for visualization purposes only.

Discussion

In this paper, we introduced *STEMorph*, a newly developed stimulus set based on the NimStim dataset, featuring facial expressions transitioning from anger to happiness . We employed neutral-anchored morphing and neural-network-generated masking and evaluated the validity and reliability of this dataset.

Participants' subjective ratings showed a robust positive correlation with the intended emotional states, indicating that our morphing methodology successfully created a naturalistic continuum of emotional transformations. This finding aligns with prior research emphasizing the importance of realistic stimuli in emotion recognition studies (15). Moreover, *STEMorph* addresses limitations in earlier datasets, such as artifacts caused by basic morphing techniques (12), thereby enhancing ecological validity.

Furthermore, STEMorph's ability to capture gender differences in emotion recognition provides a valuable tool for addressesing gaps in gender-specific emotion perception research. These results align with previous studies suggesting that facial emotion recognition is influenced by the gender of the stimuli (34) and the perceiver (35-37). Prior research have consistently reported gender-based variations in emotion recognition (17) highlighting the importance of using stimuli that account for such differences. Additionaly, the high test-retest reliability observed in our study suggests minimal variability in interpretations across multiple exposures. This finding underscores the importance of well-designed stimuli in yielding consistent results in emotion perception research.

Our methodological choices also reflect advancements over traditional approaches. Specifically, utilizing a neutral expression as an intermediary anchor point minimized bias at the central position and facilitated smoother transitions between angry and happy expressions. This approach aligns with findings from earlier studies exploring emotional gradients (2) and builds on work demonstrating that neutral anchoring enhances naturalism in morphed stimuli (11). Additionally, by generating distinct neural-network-based masks for each image, we mitigated issues like distortions

in non-facial regions (e.g., hair or ears), which are common in datasets relying on simpler masking techniques (16). Moreover, while removing the background may reduce the real-world context of the stimuli, this step eliminates distractions, focusing solely on facial features for emotion recognition. These innovations ensure that *STEMorph* preserves anatomical fidelity while maintaining focus on facial features critical for emotion recognition.

Importantly, by making the *STEMorph* stimulus set publicly available along with all associated data and codes, we facilitate broader adoption and encourage further research in this critical domain of human interaction. This transparency aligns with calls within the literature for accessible resources to advance emotion recognition studies (9). Furthermore, *STEMorph's* design principles could inform future efforts to create ecologically valid stimuli for diverse applications, including clinical diagnostics and machine learning algorithms for facial expression analysis.

Despite these strengths, this study has limitations that warrant consideration. While our strong linear relationships provide a promising foundation for future research, further examination across diverse samples is essential to assess the generalizability and external validity of our findings. For instance, expanding participant demographics beyond young adults of similar ethnic backgrounds could reveal how age or cultural differences influence emotion perception biases. Additionally, restricting participant evaluations to a scale from anger to happiness may simplify responses. Nontheless, we believe that focusing on the anger-happiness continuum provides a foundation for future studies exploring other emotional transitions with more flexible response formats. Emotions such as sadness or fear may exhibit unique perceptual biases requiring tailored stimulus sets. Therefore, developing complementary transitions between various emotions could enrich our understanding of emotion recognition processes across different contexts.

In conclusion, our results underscore the importance of methodological rigor in stimulus design within the field of emotion recognition. The incorporation of neutral-anchored morphing and neural-network-generated masks effectively addresses limitations observed in earlier studies regarding

the unnatural appearance of stimuli. By enhancing the naturalism and coherence of facial stimuli, our work significantly contributes to the ongoing efforts to improve methodologies in studying facial expressions. Furthermore, variations in emotional ratings across gender subgroups highlight the relevance of considering both participant and facial expressor characteristics in emotion recognition research. We believe that *STEMorph* can serve as a valuable resource for future studies exploring the dynamics of emotion perception across diverse populations.

Declarations

Funding

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Conflicts of interest

The authors have no competing interests to declare that are relevant to the content of this article.

Ethics approval

Approval was obtained from the ethics committee of Shahid Beheshti University of Medical Sciences (IR.SBMU.MSP.REC.1396.757). The procedures used in this study adhere to the tenets of the Declaration of Helsinki.

Consent to participate

Informed written consent was obtained from all individual participants included in the study.

Consent for publication

Facial stimuli were reused from the NimStim Set of Facial Expressions (22), in which participants provided informed consent for the publication of their facial images, covering their reuse.

Data and Code availability

The data acquired and codes for the psychophysics task and data analysis performed in this study can be found in the following GitHub repository: https://github.com/Mekatebi/STEMorph

To use the stimulus set, visit the *NimStim Set of Facial Expressions* website and follow the instructions to request access: https://danlab.psychology.columbia.edu/content/nimstim-set-facial-expressions

The stimulus set is also available from the corresponding author on reasonable request.

Author Contributions

MEK and MHG performed research, MEK analyzed data, all designed research and wrote the paper.

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