Cues driving trait impressions in naturalistic contexts are sparse

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Abstract

Trait impressions are ubiquitous and shape consequential decisions. Prior work investigated what information people used for trait impressions using artificial designs. To advance a naturalistic understanding, we applied novel computational tools to quantify comprehensive cues based on prior theories (facial, bodily, clothing, environmental cues) (Study 1) and manipulate individual cues realistically (Study 2) in naturalistic images. Across two pre-registered studies (N_1 = 2,435 U.S. representative; N_2 = 569), we found that with rich information available, the cues predicting trait impressions were sparse. We confirmed for a subset of cues that these predictions were causal. Predictive cues carried unique information beyond the consistent information shared with other available cues. Unpredictive cues played a role by shaping the utilization of predictive cues through interactions. Together, our findings suggest that the mind may have evolved to utilize the naturalistic relations between cues to simplify what information to attend to when forming trait impressions.

Keywords

trait impression, person perception, social cognition, computational modeling, naturalistic design

Teaser

In naturalistic contexts people use only a small number of cues to form trait impressions even when rich cues are available.

Introduction

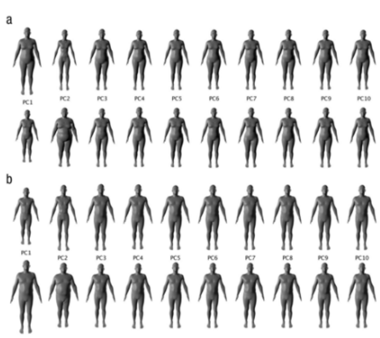
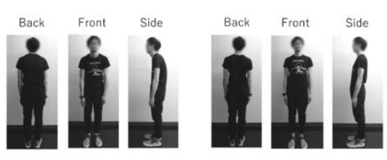
Imagine walking past a stranger on the street: you would likely observe what they look like physically, what they are doing, and what environment they are in. Most of the time, our mind does not stop at merely observing these visible cues, but attempts to infer from them characteristics of the individual: is the person attractive, warm, or competent? These trait impressions are formed very rapidly: after a 33-millisecond exposure to a face image, people are able to form trait impressions of the person that are consistent with those they form when given more time to look at the face (*1*, *2*). Although formed rapidly and often do not reflect the truth, these trait impressions profoundly influence behavior, such as mating choice (*3*), cooperation (*4*), and voting decision (*5*). How do people form these trait impressions?

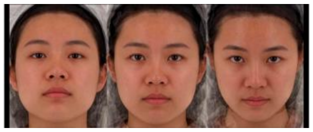
In sharp contrast to the rapid processing time, the amount of information that people may need to process to form trait impressions could be immense. For example, prior work showed that facial structural features such as facial width-to-height ratio and emotional cues such as structural resemblance to happiness predict impressions of trustworthiness (*6–10*). Body morphology such as body shape and dynamic cues such as postures and actions were found to shape impressions of competence and warmth (*11–20*). Clothing including all modifications and supplement to the body (*21*) such as hair and clothing style and color also plays a critical role in trait impressions in particular attractiveness (*22–26*). Environmental information including physical (e.g., space, objects, threat, color) and social (e.g., other people) cues were also shown to further influence trait impressions (*26–30*).

Although a large number of cues were found to shape trait impressions in prior research (Table 1), given the limited cognitive resources of the mind, it is unlikely that people use all those cues to form trait impressions when rich cues are simultaneously available in naturalistic contexts. Indeed, vision research has long shown that people do not process all the available visual cues, but only attend to important information according to the situation (*31–34*). The many important cues found in prior research may instead be attributed to the artificial designs they used. For example, prior work typically emphasizes the cue of interest in their stimuli in isolation of other cues (e.g., using facial images in isolation of the body to examine the effects of facial cues on trait impressions). However, the importance of a cue is influenced by the other cues available (*28*, *35–37*). For instance, when people are presented with the face and body together, body becomes a more salient cue that shapes ability-related impressions while the importance of facial cues is greatly reduced (*38*). Thus, prior conclusions predominantly derived based on examination of cues in isolation may not capture what information people use to form trait impressions in naturalistic contexts.

Forming trait impressions based on a combination of cues is distinct from combining the trait impressions formed based on each cue (*39*, *40*). Human perception does not reflect the state of the world objectively; instead, the mind interprets the physical signals received (*41*). Such interpretation is influenced by other visual inputs that are simultaneously present. A classic example is color constancy: when illumination changes, people may perceive the same color as different (*42*). This phenomenon also exists in social perception (*43*): for instance, a face that looks angry when perceived in isolation may be perceived as feeling surprised instead when observed in the context of a birthday party (Fig.1A). Some studies have investigated how people form impressions based on multiple cues (*36*, *37*, *44*), but they often relied on artificial combinations of cues (e.g., an isolated face put on top of an unrelated scene, actors and actresses posed in scenes, computationally generated avatars). These designs may distort the naturalistic relations between cues, precluding a more ecologically valid mechanism of trait impressions.

Table 1. Rich cues found important to trait impressions in prior research

Category	Stimuli	Measure	Conclusion
Facial Cues	Jaeger & Jones (2022) (7) used face images from the Chicago Face Database (45). Each target showed a neutral facial expression and wore a gray shirt, photographed from a fixed distance against a uniform background	Elastic Net models with nested cross-validation were used to estimate the predictive power of 28 features, such as emotion cues and facial width-to-height ratio, on trustworthy and dominant impressions	***Emotion*** resemblances were the most predictive of both trustworthiness and dominance.
	 Fink et al., (2006) (46) used 3D female faces with same shapes and different skin color distributions	Correlations between real age (captures age-related changes of skin color distribution) and participants' trait ratings	***Skin Color*** distribution shaped the perception of attractiveness, health, and youthfulness of female faces
	 Keles et al., (2021) (8) used face images from the Chicago Face Database (45) with different manipulations: (a) original, (b) grey, (c) grey + masked, (d) grey + masked + equalized	Deep convolutional neural networks (DCNNs) were used to extract facial structural features and Ridge regressions with cross-validation were used to predict trait ratings using those features	***Facial Structural*** features from DCNNs pre-trained to distinguish facial identities predicted trait impressions
	Cook & Smith et al. (1975) (47) used real human confederates to display different gaze directions: averted, normal, continueous	Each participant interacted with three confederates in different gaze conditions and rated traits impression of these confederates	The amount of ***Gaze*** affected impressions: more gaze, more favorable impressions
Bodily Cues	 Hu et al. (2018) used artificial body images that differ in body shapes	Participants rated each body shape on a range of traits; correspondence analysis was used to create low-dimensional spaces separately for male and female bodies based on their perceived traits	***Body Shape*** influenced the traits people infer from the individual
	 Kitamura & Watanabe (2021) (48) used photos of real individuals in different poses in three vieweing angles (back, front, side)	Participants rated their impressions on various traits for the target with "good" or "bad" postures in three viewing angles of the same persons	***Body Pose*** affects trait impression: "good" postures perceived as more attractive and trustworthy than "bad" postures

	 Zhang et al. (2022) (49) used faces with up, neutral, and down posture	Participants rated the cooperativeness of the three postures of the same faces	***Head Pose*** affects perceived cooperativeness: neutral level perceived as more cooperative than head up or down
	 Fiedler et al. (2005) (12) used degraded pictures dipicting a subject's action towards an object person	Participants viewed the pictures, then completed an encoding task (verifying graphical features or semantic interpretations), then identify gradually unmasked trait words	***Action*** leads to spontaneous encoding of trait impressions
Clothing Cues	Behling & Williams (1991) (22) used black and white photographs of a male and a female high school student with four clothing style (dressy, artsy, casual, and hood).	High school students and teachers rated the intelligence and academic achievement of the targets	***Clothing Style*** influenced the perception of intelligence and academic achievement
	 Pazda & Thorstenson (2019) (50) used headshots of same individuals in different clothing colors	Participants rated the perceived personality traits of the target individuals	***Clothing Color*** intensity increases perceived extraversion and openness
	 Fink et al. (2016) (51) used images of vitual hair manipulated in colors	Participants rated the perceived age, health, and attractiveness of hair images	***Hair Color*** shapes perceptions of age, health, and attractiveness
	 Fink et al. (2016) (51) used images of vitual hair manipulated in styles	Participants rated the perceived age, health, and attractiveness of hair images	***Hair Style*** shapes perceptions of age, health, and attractiveness
Environment	 Pazda & Thorstenson (2019) (50) used headshots of same individuals with borders of different colors	Participants rated the perceived personality traits of the target individuals	***Environmental Color*** intensity increases perceived extraversion and openness
	Gosling et al. (2002) (27) used photos of real participants' offices and bedrooms	Participants rated the big five personality traits based on the photos; researchers manually	Environmental cues such as ***Complexity*** (how many items, how organized or cluttered),

		rated the presence of various cues from the space (such as environmental complexity, gist, vibe)	***Gist*** (multi- or single-purpose, public or private space), and ***Vibe*** (how cheerful and comfortable the space is)
Interaction of Different Cue Categories	 Hu & O'Toole (2023) (36) used images of actors and actresses with face, body, or whole person visible	Participants rated 17 traits based on the stimuli; correspondence analysis was used to visualize the global structures of the trait inferences from faces, bodies, and the whole persons	***Body and Face*** impressions assimilate to each other: Agreeableness traits primarily inferred from faces; conscientiousness traits from the body; extraversion traits from the whole person
	 Bjornsdottir et al. (2024) (52) used images depicting targets with different poses (neutral vs spontaneous) and clothing (without vs with clothing)	Participants evaluated demographic and trait impressions. Intraclass correlation coefficients were computed to quantify the proportion of variance in the impression attributable to difference sources	***Face, Body, and Clothing*** contribute distinctly to different trait impressions
	 Mattavelli et al., (2023) (28) used computer-generated faces with two expressions (happy vs. fearful) in two contexts (threat vs no context).	Participants rated trustworthiness of the stimuli	***Facial Emotions and Environment*** interacted: negative impacts of contextual threat on perceived trustworthiness were stronger for happy than fearful faces
	 Küster et al. (2018) (53) used computationally generated avatars in different body poses (open vs close) of different clothing (nurse vs military)	Participants rated the empathy and dominance of the stimuli	***Body Pose and Clothing*** interacted: body pose moderated the effect of clothing on impressions

Thus, despite a large literature, it remains an open question what visual cues people use to form trait impressions in naturalistic contexts. This gap in the literature largely stems from the lack of tools to quantify and manipulate naturalistic cues. Prior work predominantly relied on human coders to quantify information in naturalistic stimuli that participants may use for forming trait impressions (e.g., rating how cheerful or comfortable the environment is in a photo)

(*27*). The advantage of this method is that the quantifications of cues take into account the interaction effects of other available cues since they are human interpretations of a particular cue in the full context (Fig. 1B). However, since it is based on human interpretations, the dimensions along which a cue (e.g., body poses) can be quantified are constrained to only those interpretable by humans (e.g., open versus close poses), which may not sufficiently capture the variability of a cue in naturalistic contexts (the many other ways body poses could differ from one another). Existing methods for manipulating visual cues are also limited in naturalistic contexts, prompting most researchers to rely on computationally generated images (e.g., computationally generated faces that differ in skin color only) and artificially combined stimuli (e.g., combining different faces with different bodies) which are more controllable but less realistic.

To advance a more complete understanding of what information is used to form trait impressions in naturalistic contexts, here we meet the technical challenges by leveraging a wide range of novel computational tools (*54*). In Study 1, we apply computational tools to quantify a comprehensive set of cues found important in prior research (Fig. 1C). In brief, these algorithms were trained to extract the most relevant information of a cue (e.g., body pose) so that they best distinguish variations in this cue (e.g., different body poses). Since the algorithms were trained based on human-generated labels (e.g., labeling different body poses) using naturalistic images, the resulting quantifications take into account the context in which the target cue was perceived (Fig. 1B). Although human labels were used in training, the resulting quantifications may not be interpretable: for instance, the variation in body poses can be captured by the distances between joint locations in a three-dimensional space; but different from the interpretable features such as openness or closeness of body pose, these distances may not be captured by existing concepts in human language (e.g., the distance between the right elbow and the right hipbone).

In Study 1, we applied these computational tools to annotate rich cues in a diverse set of naturalistic images (N = 1,125). These images portray individuals of diverse demographics who were captured spontaneously or posed for photos in a wide range of everyday scenarios. We verified that the computationally extracted quantifications described meaningful variations in each cue (Fig. 2A-F). For the cues failed to capture by computational tools (Fig. 1C), we relied on human annotations from a large sample of U.S. representative participants (N = 1,530). In total, a comprehensive set of 16 cues proposed to be important based on prior theories (Table 1) were quantified (Fig. 1C). These 16 cues (i.e., "fine-grained cues") can be grouped into four categories (i.e., "coarse-category cues") according to tradition: face, body, clothing, and environment. To account for the interactions between cues, all quantifications were performed in context without cropping out the target cue in isolation (Fig. 1A-B).

To maximize the comprehensiveness of our study, we identified a range of traits center to social cognition across five major theories (Fig. 1D). Warmth and competence were chosen from the stereotype content model (*55*) which posits that these two dimensions summarize perceptions of the self, others, and groups. Dominance was selected from the two-dimensional face-trait model (*56*) which proposes that warmth/valence and dominance are key to face perceptions. Femininity and youthfulness were added from the four-dimensional face-trait model (*57*) which proposes that warmth, competence, femininity, and youthfulness underlie a wide range of trait impressions. Openness was from the Big Five personality model (*58*) and selected based on the correlations between Big Five traits and the traits already included: openness was the only trait with low correlation with the traits already included in the four-dimensional face-trait model. Finally, we added attractiveness, whose perception, together with femininity and youthfulness, is believed to have evolutionary functions (*59*) (e.g., identifying good fitness for reproduction).

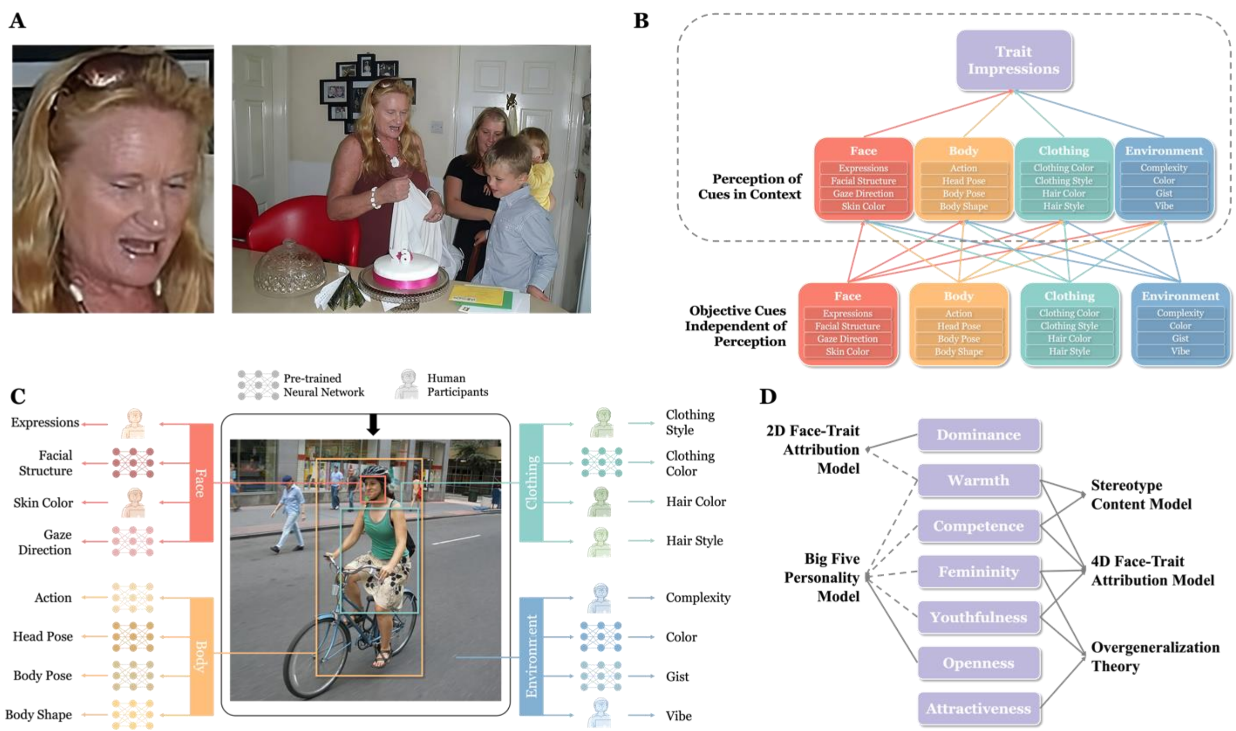


Fig. 1. Research Design of Study 1. (A) An example illustrating that a face shown in isolation may be perceived differently when shown in context. (B) Relationships between objective cues, perceived cues, and trait impressions. The current study focused on the dotted region. (C) Quantifying comprehensive visual cues proposed by prior theories using a range of computational algorithms and human annotations (for cues where computational tools performed poorly). To quantify cues as perceived in context as in (B), all quantifications were based on the target cue together with the context (e.g., the entire image for human annotations; the entire target person with context for body annotations). Computationally quantified features are often uninterpretable individually (except for gaze direction, with features of frontal, left, right, up, down, and closed) but can be interpreted as a collection across features (see Fig. 2). Human annotations were based on interpretable features: 8 emotions (disconnection, esteem, anger, aversion, fear, happiness, sadness, surprise); 10 skin color shades (10 color blocks from light to dark); 4 clothing styles (formal, provocative, feminine, masculine); 3 hair styles (formal, provocative, feminine, masculine); 5 hair color (black, brown, red, blond, white); 2 complexity (number and organization of items); and 2 gist (threat/non-threat, positive/negative). (D) Seven traits selected based on major theories of social cognition. Solid lines indicate the exact labels used in the theories; dotted lines indicate terms highly similar to the labels used in the theories.

Fig. 2. Validation of Computationally Quantified Cues. For quantifications that are not easily interpretable (e.g., facial structure for which the number of features is large, 512, and each feature is not interpretable), we conducted principal component analysis (PCA) on all the features of the cue (e.g., all the 512 features of facial structure) across our 1,125 naturalistic images. The PCs summarize the dimensions along which the target cue varied the most among our images. Each panel plots the top PCs per cue. Each row plots the examples with the highest (left) and lowest PC scores (right). Only one validation is shown for cues quantified with the same algorithm (body pose and head pose; clothing color and environment color). Cues quantified with interpretable features were validated per feature without PCA (gaze direction).

We collected ratings from U.S. representative participants (N = 990) on these traits for target individuals in naturalistic images (N = 1,125) and investigated how well these impressions can be predicted by the comprehensive set of cues quantified from the images. We tested four pre-registered hypotheses in Study 1. First, how consistent naturalistic trait impressions are across perceivers. Prior work using constrained stimuli (e.g., isolated faces) showed that trait impressions had a high consensus across perceivers (*57*, *60*). But it remains unclear whether this conclusion generalizes to trait impressions made from more complex stimuli. A high consensus between perceivers would suggest a shared mechanism underlying trait impressions. Second, we investigated this shared mechanism using aggregate-level ratings across participants of the targets. We analyzed how well each cue (coarse-category and fine-grained) predicted trait impressions. To obtain a more accurate estimate given the multicollinearity between cues, we regressed impressions of a trait on each cue in separate models. To handle the high-dimensional nature of the cues (some cues had a greater number of features than the number of stimuli), we modeled the relationship between cues and impressions using representational similarity analysis (RSA): if a cue is used to form trait impressions, the more similar two target individuals are in terms of this cue, the more similar impressions they should elicit. To maximize out-of-sample generalizability, we combined RSA with Ridge regression with cross-validation procedures. We used maximal statistic permutation tests to estimate the significance of the predictions and correct for multiple testing across cues (see Materials and Methods).

Third, given the importance of each cue, we investigated whether this importance can be explained by the information that is unique to the cue. If different cues in naturalistic contexts tend to carry similar information for trait impressions (*61*, *62*), people may not need to process all the cues that are available but only those that carry unique information beyond other cues. To this end, we regressed impressions on all the cues in the same model and compared how much predictions dropped when a specific cue was removed, which indicated the unique contribution of the left-out cue (i.e., variance partition analysis, see Materials and Methods). Finally, we investigated whether for the cues that are not directly predictive of impressions, they still play a role in shaping impressions by interacting with the cues that are predictive. For instance, the perception of an important cue may be influenced by other cues that are simultaneously present, leading to an indirect role of those cues on trait impressions. To this end, we conducted two-way interaction analyses to estimate the interactions between all pairs of cues.

Given the complex shared information and interactions between cues, it is necessary to confirm that the predictions found in Study 1 indicate that people indeed use those predictive cues to form trait impressions. Study 2 investigated whether the predictions found in Study 1 were causal by digitally manipulating a single predictive cue at a time in the naturalistic images. One major motivation for prior work to rely on relatively simple stimuli is that those stimuli are well suited for controlled experimental manipulations, which are crucial for identifying causal effects (*63*). Here, we show that with the advances in artificial intelligence, such experimental manipulation is also possible with complex, naturalistic images. Specifically, we identified a subset of fine-grained cues to manipulate according to the following criteria: i) diversified the coarse categories they belong to; ii) diversified the trait impressions predicted; iii) had unique explained variance; iv) the effects of all features belonging to a cue were congruent; and that v) state-of-the-art algorithms were able to manipulate this cue realistically without distorting other cues in the naturalistic images. This procedure selected a final set of two cue-trait pairs whose causal effects we tested in Study 2: the effect of facial expressions of emotions on perceived warmth, and the effect of clothing style on perceived attractiveness. We manipulated these two cues on a sufficiently powered subset of 147 images from Study 1, which were systematically selected using the maximum variation sampling procedure to convey the most distinct visual information along the 16 cues (see Materials and Methods).

All studies were pre-registered and the registrations can be accessed at the Open Science Framework: https://osf.io/km5fa/?view_only=8c6a128ddd884461926c6baa929eb08c for Study 1; https://osf.io/jnp24/?view_only=665c756249af4a9292a638c8ce29cc63 for Study 2. There was no deviation from the preregistrations. All data and code are available at Open Science Framework as well: https://osf.io/jp2hn/?view_only=207af00c5d72484e98d7415c6fc78303. Participants in all studies provided informed consent in a manner approved by the Institutional Review Board of University of California San Diego (808857).

Results

Trait Impressions from Naturalistic Images Had High Consensus

We quantified the consensus among participants using the split-half reliability measure as pre-registered. We found a high consensus for all the 7 trait impressions (Fig. 3A). These findings suggest that different perceivers may use similar information in a similar way to form trait impressions from naturalistic images. Given the high consensus, we aggregated the ratings across participants per image and confirmed that the relations between different trait impressions were in the expected direction (Fig. 3B). Together, these results confirmed that people formed reliable trait impressions (regardless of their validity) from naturalistic images for a range of traits.

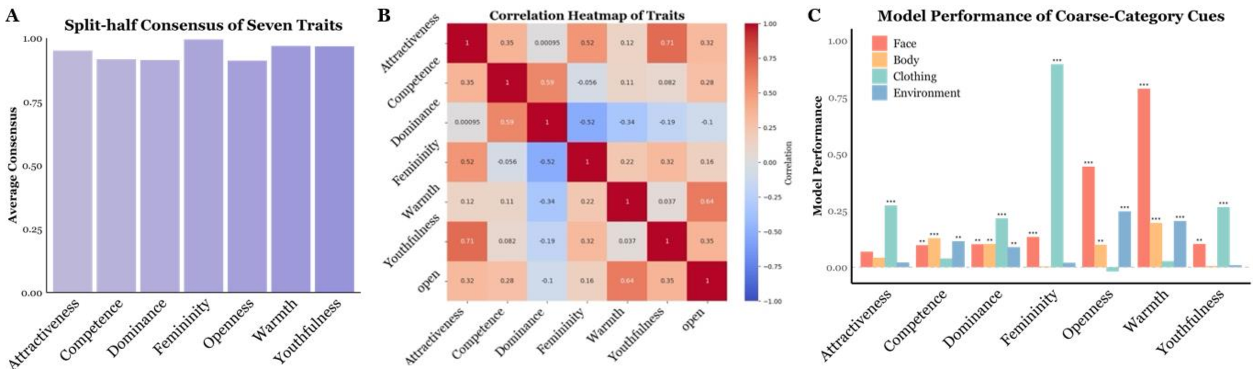


Fig. 3. Reliability and coarse-category cue predictions for naturalistic trait impressions. (A) Split-half consensus among participants per trait impression (N ≥ 42 participants per image per trait). (B) Pearson correlations between aggregate-level ratings of different trait impressions (N = 1,125 images). (C) Model prediction accuracy per trait impression (x-axis) per coarse-category cues (colors). Representational similarity with Ridge regression and cross-validation was used to assess the prediction across image pairs (N = 632,250 pairs). Each model regressed the distances in the trait impressions on the distances in all the features belonging to a given coarse-category cue. Model accuracy was assessed with the Pearson correlation between predicted and observed trait ratings for the images in the test set. Bar heights indicated the mean prediction accuracies ($\bar{r}$) across 500 cross-validation iterations. Prediction significance was estimated and corrected for multiple testing using maximal statistic permutation tests: *$p < .05$, **$p < .01$, ***$p < .001$.

A Sparse Set of Cues Predicted Impressions of Each Trait

Given the high consensus across participants, we analyzed the shared mechanism at the aggregate level in all subsequent pre-registered analyses. For each cue and each trait impression, we analyzed whether the more similar the cue was between two target individuals the more similar trait impressions they elicited using representational similarity analysis with Ridge regression and cross-validation to increase generalizability. For coarse-category cues, we found that even though all these cues were proposed to be important to trait impressions in prior research, for the majority of the traits (6 out of 7 traits), not all of the coarse-category cues significantly predicted the trait impression (Fig. 3C; see Table S1 for detailed statistics). As pre-registered, we also compare the prediction accuracy of the face (the most studied stimuli in the literature) to those of body, clothing, and environmental cues. The prediction from the face was significantly greater than that from the body for four of the trait impressions: warmth (difference in mean prediction accuracy across cross-validation iterations $\Delta\bar{r} = .59$, $p = .0005$, SD = ±0.03), openness ($\Delta\bar{r} = .34$, $p = .0005$, SD = ±0.05), femininity ($\Delta\bar{r} = .13$, $p = .0005$, SD = ±0.02), and youthfulness ($\Delta\bar{r} = 10$, $p = .001$, SD = ±0.03); greater than the prediction from clothing for three of the trait impressions: warmth ($\Delta\bar{r} = .76$, $p = .0005$, SD = ±0.03), openness ($\Delta\bar{r} = .42$, $p = .0005$, SD = ±0.04), and competence ($\Delta\bar{r} = .06$, $p = .04$, SD = ± 0.04); and greater than the prediction from environment on four of the trait impressions: warmth ($\Delta\bar{r} = .58$, $p = .0005$, SD = ±0.04), openness ($\Delta\bar{r} = .20$, $p = .0005$, SD = ±0.05), femininity ($\Delta\bar{r} = .11$, $p = .0005$, SD = ±0.02), and youthfulness ($\Delta\bar{r} = .09$, $p = .001$, SD = ±0.02). However, the prediction from the face was significantly smaller than that from clothing for four trait impressions: femininity ($\Delta\bar{r} = .\text{-}76$, $p = .0005$, SD = ±0.02), attractiveness ($\Delta\bar{r} = -.20$, $p = .0005$, SD = ±0.04), youthfulness ($\Delta\bar{r} = -.16$, $p = .0005$, SD = ±0.03), and dominance ($\Delta\bar{r} = -.11$, $p = .0005$, SD = ±0.05). These findings suggest that cue importance found in prior research where target cues were examined in isolation may not generalize to naturalistic contexts. For instance, while isolated face images were frequently used for attractiveness perception and that dominance was proposed as one of the core dimensions underlying trait impressions, the face was not the most predictive cue for attractiveness and dominance when other cues were also available in naturalistic contexts.

One of the unique advantages of quantifying rich naturalistic cues in context is that we can examine the contribution of each fine-grained cue beyond those of the coarse-category cues, which was not feasible with most traditional methods such as manipulating the presence/absence of the entire coarse-category cue (e.g., adding or removing the entire body from the face). We found that only a small number of cues showed significant predictions of each trait impression (Fig. 4; see Table S2 for detailed statistics). Physical-related impressions, including femininity, youthfulness, and attractiveness, were significantly predicted by hair color ($\bar{r}$ = .09, p = .0005 for femininity; $\bar{r}$ = .26, p = .0005 for youthfulness; $\bar{r}$ = .10, p = .017 for attractiveness). Impressions of femininity and youthfulness were also predicted by facial structure ($\bar{r}$ = .13, p = .0005 for femininity; $\bar{r}$ = .11, p = .007 for youthfulness). Impressions of femininity and attractiveness were also predicted by hair style ($\bar{r}$ = .88, p = .0005 for femininity; $\bar{r}$ = .25, p = .0005 for attractiveness) and clothing style ($\bar{r}$ = .76, p = .0005 for femininity; $\bar{r}$ = .24, p = .0005 for attractiveness). Approachability-related impressions, including warmth and openness to experience, were significantly predicted by facial expressions of emotions ($\bar{r}$ = .79, p = .0005 for warmth; $\bar{r}$ = .44, p = .0005 for openness) and environmental vibe ($\bar{r}$ = .20, p = .0005 for warmth; $\bar{r}$ = .25, p = .0005 for openness). Impressions of warmth were also predicted by actions ($\bar{r}$ = .19, p = .0005) and gaze directions ($\bar{r}$ = .09, p = .0005). Power-related impressions, including competence and dominance, were significantly predicted by action ($\bar{r}$ = .13, p = .003 for competence; $\bar{r}$ = .11, p = .018 for dominance). Impressions of dominance were also predicted by clothing style ($\bar{r}$ = .21, p = .0005) and hair style ($\bar{r}$ = .19, p = .0005). These results suggest that when rich information is available in naturalistic contexts, only a very small number of cues (less than 4 out of 16 for every one of the 7 traits) that are most informative for a given trait are linked to impressions of the trait. These predicted fine-grained cues were not constrained to only a specific coarse category, but distributed across face, body, clothing, and environmental cues depending on the specific trait. The predicted fine-grained cues were not constrained to only interpretable/human quantified features nor only computationally extracted features either, but instead distributed across both types of quantifications across the different traits.

Fig. 4. Prediction accuracy of each fine-grained cue for each trait impression. Each model (each bar) regressed distances in a trait impression on distances in all features belonging to a

fine-grained cue across image pairs (N = 632,250) using representational similarity analysis with Ridge regression and cross-validation to increase generalizability. Bar heights indicate the mean prediction accuracy ($\bar{r}$) across 500 cross-validation iterations where the prediction accuracy was computed as the Pearson correlation between the predicted and observed rating distances for the image pairs in the test data. The significance of the prediction accuracy and the correction for multiple testing across cues were calculated using the maximal statistic permutation tests (see Materials and Methods) and indicated by the asterisks: *$p < .05$, **$p < .01$, ***$p < .001$.

Predictive Cues Carried Unique Information Beyond Other Cues

Given the sparsity of cue prediction, we analyzed whether those cues that showed significant predictions were important because they carried unique information that could not be explained by other co-occurring cues in the naturalistic images. For each trait impression, we analyzed how much the explained variance (magnitude of the squared prediction accuracy, $|\bar{r}|^2$) of the model dropped when removing a particular cue from all the rest of the cues in the model. This explained variance drop can be attributed to the unique information carried by the removed cue. As pre-registered, we performed this analysis only for cues that were found predictive (see Fig. 3C and Fig. 4). We found that, for the coarse-category cues, 15 out of the 18 predictive cases across traits were where the coarse-category cue had a statistically significant unique explained variance over the rest of the coarse-category cues (Fig. 5A; see Table S3 for detailed statistics). The face conveyed unique information beyond body, clothing, and environmental cues for its predictions of perceived warmth ($\Delta|\bar{r}|^2 = 0.55$, $p = .0005$), openness ($\Delta|\bar{r}|^2 = 0.15$, $p = .0005$), youthfulness ($\Delta|\bar{r}|^2 = 0.007$, $p = .0005$), and dominance ($\Delta|\bar{r}|^2 = 0.004$, $p = .023$), and femininity ($\Delta|\bar{r}|^2 = 0.00038$, $p = .041$). The body conveyed unique information beyond face, clothing, and environmental cues for its predictions of perceived competence ($\Delta|\bar{r}|^2$ = 0.009, p = .0005), dominance ($\Delta|\bar{r}|^2$ = 0.006, p = .004), and warmth ($\Delta|\bar{r}|^2$ = 0.002, p = .009). Clothing conveyed unique information beyond face, body, and environmental cues for its predictions of perceived femininity ($\Delta|\bar{r}|^2$ = 0.784, p = .0005), attractiveness ($\Delta|\bar{r}|^2$ = 0.070, p = .0005), youthfulness ($\Delta|\bar{r}|^2$ = 0.066, p = .0005), and dominance ($\Delta|\bar{r}|^2$ = 0.042, p = .0005). The environment conveyed unique information beyond face, body, and clothing for its predictions on perceived openness ($\Delta|\bar{r}|^2$ = 0.017, p = .0005), competence ($\Delta|\bar{r}|^2$ = 0.008, p = .0005), and dominance ($\Delta|\bar{r}|^2$ = 0.004, p = .037). These findings suggest that cues that are important for trait impressions in naturalistic contexts carry unique information beyond other available cues.

Using the same variance partition analysis, we also examined the unique explained variances of each fine-grained cue that was found to be predictive of trait impressions (Fig. 4). We found that 14 out of the 19 predictive cases were where the fine-grained cue had a statistically significant unique explained variance over the rest of the fine-grained cues (Fig. 5B; see Table S4 for detailed statistics). Facial structural cues conveyed unique information beyond the other 15 cues for its predictions of perceived youthfulness ($\Delta|\bar{r}|^2$ = 0.007, p = .0005) and femininity ($\Delta|\bar{r}|^2$ = 0.001, p = .016). Facial expressions of emotions conveyed unique information beyond the other 15 cues for its predictions of perceived warmth ($\Delta|\bar{r}|^2$ = 0.546, p = .0005) and openness ($\Delta|\bar{r}|^2$ = 0.150, p = .0005). Action cues conveyed unique information beyond the other 15 cues for its predictions of perceived competence ($\Delta|\bar{r}|^2$ = 0.008, p = .001) and dominance ($\Delta|\bar{r}|^2$ = 0.006, p = .004). Clothing style and hair style each independently conveyed unique information beyond the other 15 cues for its predictions of perceived femininity ($\Delta|\bar{r}|^2$ = 0.030, p = .0005 for clothing style; $\Delta|\bar{r}|^2$ = 0.212, p = .0005 for hair style) and attractiveness ($\Delta|\bar{r}|^2$ = 0.005, p = .011 for clothing style; $\Delta|\bar{r}|^2$ = 0.011, p = .0005 for hair style).

Clothing style also conveyed unique information beyond the other 15 cues for its predictions of perceived dominance ($\Delta|\bar{r}|^2$ = 0.011, p = .0005). Hair color conveyed unique information beyond the other 15 cues for its predictions of perceived youthfulness ($\Delta|\bar{r}|^2$ = 0.062, p = .0005) and attractiveness ($\Delta|\bar{r}|^2$ = 0.005, p = .008). Environmental vibe conveyed unique information beyond the other 15 cues for its predictions of perceived openness ($\Delta|\bar{r}|^2$ = 0.016, p = .0005). These findings confirmed that cues that are important for trait impressions in naturalistic contexts carry unique information that cannot be explained by other available cues.

Given the unique explained variance of the predictive cues, we next ask whether these cues carried only unique information or that they also share consistent information with other cues using similar variance partition analyses (see Materials and Methods). We found that, in 8 out of 18 predictive cases, coarse-category cue carried information that was shared with others (Fig. 5A). Face conveyed information in common with other cues for its predictions of perceived warmth ($\Delta|\bar{r}|^2$ = 0.071, p = .0005), openness ($\Delta|\bar{r}|^2$ = 0.042, p = .0005), and femininity ($\Delta|\bar{r}|^2$ = 0.017, p = .0005). Body and environment conveyed information in common with other cues for its predictions of perceived warmth ($\Delta|\bar{r}|^2$ = 0.033, p = .0005 for body, $\Delta|\bar{r}|^2$ = 0.038, p = .0005 for environment) and openness ($\Delta|\bar{r}|^2$ = 0.004, p = .015 for body, $\Delta|\bar{r}|^2$ = 0.036, p = .0005 for environment). Clothing conveyed information in common with other cues for its predictions of perceived femininity ($\Delta|\bar{r}|^2$ = 0.016, p = .0005).

For the fine-grained cues, in 16 out of the 19 predictive cases, the fine-grained cue also carried information that was shared with at least one of the other cues available (Fig. 5B). Facial structure conveyed information in common with other cues for its predictions of perceived femininity ($\Delta|\bar{r}|^2$ = 0.017, p = .0005). Facial expressions of emotions conveyed information in common with other cues for its predictions of perceived warmth ($\Delta|\bar{r}|^2$ = 0.072, p = .0005) and openness ($\Delta|\bar{r}|^2$ = 0.042, p = .0005). Gaze direction conveyed information in common with other cues for its predictions of perceived warmth ($\Delta|\bar{r}|^2$ = 0.005, p = .0005). Action conveyed information in common with other cues for its predictions of perceived warmth ($\Delta|\bar{r}|^2$ = 0.033, p = .0005) and competence ($\Delta|\bar{r}|^2$ = 0.004, p = .003). Clothing style conveyed information in common with other cues for its predictions of perceived femininity ($\Delta|\bar{r}|^2$ = 0.554, p = .0005), attractiveness (($\Delta|\bar{r}|^2$ = 0.047, p = .0005), and dominance ($\Delta|\bar{r}|^2$ = 0.028, p = .0005). Hair style conveyed information in common with other cues for its predictions of perceived femininity ($\Delta|\bar{r}|^2$ = 0.560, p = .0005), attractiveness ($\Delta|\bar{r}|^2$ = 0.048, p = .0005), and dominance ($\Delta|\bar{r}|^2$ = 0.028, p = .0005). Hair color conveyed information in common with other cues for its predictions of perceived femininity ($\Delta|\bar{r}|^2$ = 0.008, p = .0005) and youthfulness ($\Delta|\bar{r}|^2$ = 0.002, p = .048). Environmental vibe conveyed information in common with other cues for its predictions of perceived warmth ($\Delta|\bar{r}|^2$ = 0.038, p = .0005) and openness ($\Delta|\bar{r}|^2$ = 0.037, p = .0005). These findings suggest that cues that are important for trait impressions in naturalistic context also tend to carry information that is congruent with other available cues.

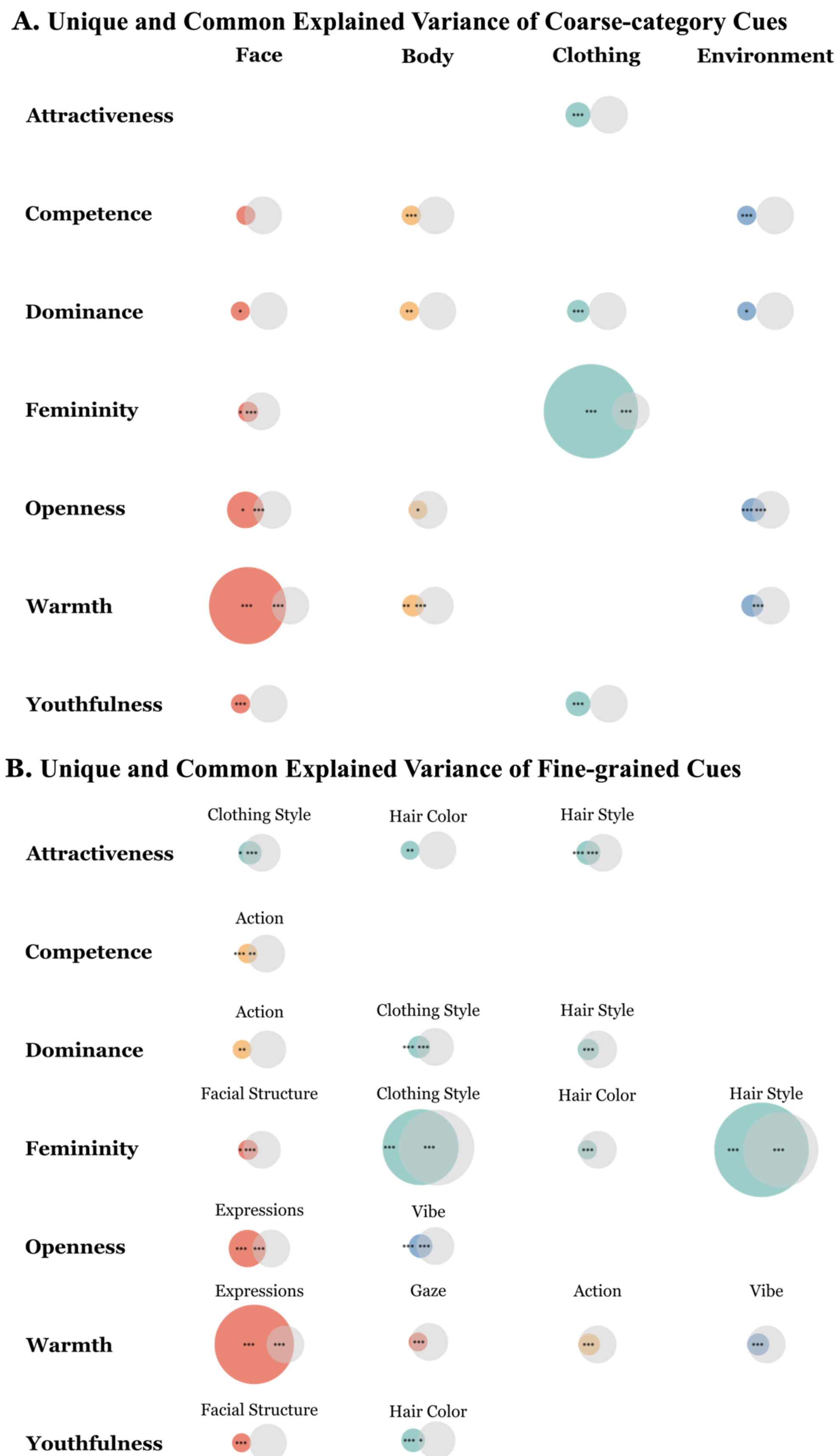

A. Unique and Common Explained Variance of Coarse-category Cues
Face
Body
Clothing
Environment
Attractiveness
Competence
Dominance
Femininity
Openness
Warmth
Youthfulness
B. Unique and Common Explained Variance of Fine-grained Cues
Attractiveness
Clothing Style
Hair Color
Hair Style
Competence
Action
Dominance
Action
Clothing Style
Hair Style
Femininity
Facial Structure
Clothing Style
Hair Color
Hair Style
Openness
Expressions
Vibe
Warmth
Expressions
Gaze
Action
Vibe
Youthfulness
Facial Structure
Hair Color

Fig. 5. Unique and common explained variance of coarse-category and fine-grained cues. Each row plots the cues that were predictive of the given trait impression. The variance partition analysis was only carried out for cues that were predictive (Fig. 3C and Fig.4) as pre-registered; cues not plotted here for a trait impression were not found predictive (Fig. 3C and Fig.4). For each trait impression and each target cue, we regressed the distances in trait impressions on the distances in i) all features across all cues (grey circles), ii) only features about a specific cue (colored circles), or iii) all features except for those about a specific cue, across image pairs (N = 632,250) using representational similarity analysis with Ridge regression and cross-validation to increase generalizability. The explained variance of each model was computed as the magnitude of its squared model accuracy, $|\bar{r}|^2$, (i.e., absolute squared Pearson correlation between the predicted and observed distances of trait ratings between image pairs in the test data). The size of the colored circles reflected the magnitudes of these explained variances of each cue in model ii). The size of the grey circles remains the same across all cues and trait impressions. Mean absolute change in model explained variance, $\Delta|\bar{r}|^2$, between model i) and model iii) indicates the unique explained variance of a given cue compared to the rest of the cues on a trait impression across the 500 cross-validation iterations. These mean unique explained variances are indicated by the non-overlapping parts of the colored circles with the grey circles. Mean absolute change in model explained variance, $\Delta|\bar{r}|^2$, between model i) and the sum of model ii) and iii) indicates the common explained variance of a given cue shared with at least one of the remaining cues on a trait impression across the 500 cross-validation iterations. These mean common explained variances are indicated by the overlapping parts between the colored circles and the grey circles. The significance of the changes in explained variance were estimated and corrected for multiple testing across cues using maximal statistic permutation tests. Statistical significance is indicated with asterisks: *p < .05, **p < .01, ***p < .001.

Nonpredictive Cues Shaped Utilization of Predictive Cues Through Interactions

Given the sparsity of cue prediction, so far, we have investigated what was special about these predictive cues – they tend to carry unique information beyond other available cues and shared information with some of the available cues for impression formation. We next investigate whether nonpredictive cues may shape utilization of predictive cues through complex interactions in naturalistic contexts. To this end, we regressed the distances in a trait impression on the distances in all cues and the two-way interactions between the cues using representational similarity analysis with Ridge regression and cross-validation. For the coarse-category cues, we found that there were significant interactions between face, body, clothing, and the environment for different trait impressions (Fig. 6; see Table S5 for detailed statistics). Most of these interactions were between two predictive cues for a trait impression. For instance, both face and body cues significantly and individually predicted perceived openness (Fig. 3C); body cues also interacted with faces cues for perceived openness: the more different two individuals' body cues were, the similarity in the perceived openness between these two individuals was more strongly linked to the similarity between their facial cues ($\beta = 0.047$, 95%CI = [0.026, 0.135]). However, some of the interactions were between a predictive cue and a nonpredictive cue. For instance, environmental cues significantly and individually predicted perceived warmth (Fig. 3C) but clothing cues did not; however, clothing cues interacted with environmental cues for perceived warmth: the more different two individuals' clothing cues were, the similarity in the perceived warmth between the two individuals was more strongly linked to the similarity between their environmental cues ($\beta = 0.022$, 95%CI = [0.008, 0.066]). Analyses of the interactions between fine-grained cues showed similar patterns (Fig. S1; see Table S6 for detailed statistics). These findings suggest that a cue that was not predictive of trait impressions directly may still influence trait impressions by modifying the effects of predictive cues.

We also found that the directions of the interaction effects were complex. Although in some cases as illustrated in the two examples above, when one cue was more different between two target individuals people rely more on the other cue to form impressions, this was not always the case. For instance, for perceived youthfulness, the more different two individuals' facial cues were, the similarity in their perceived youthfulness was less strongly linked to the similarity between their clothing cues (β = -0.057, 95%CI = [-0.120, -0.041]). Analyses of the interactions between fine-grained cues showed similar complex patterns (Fig. S1; see Table S6 for detailed statistics).

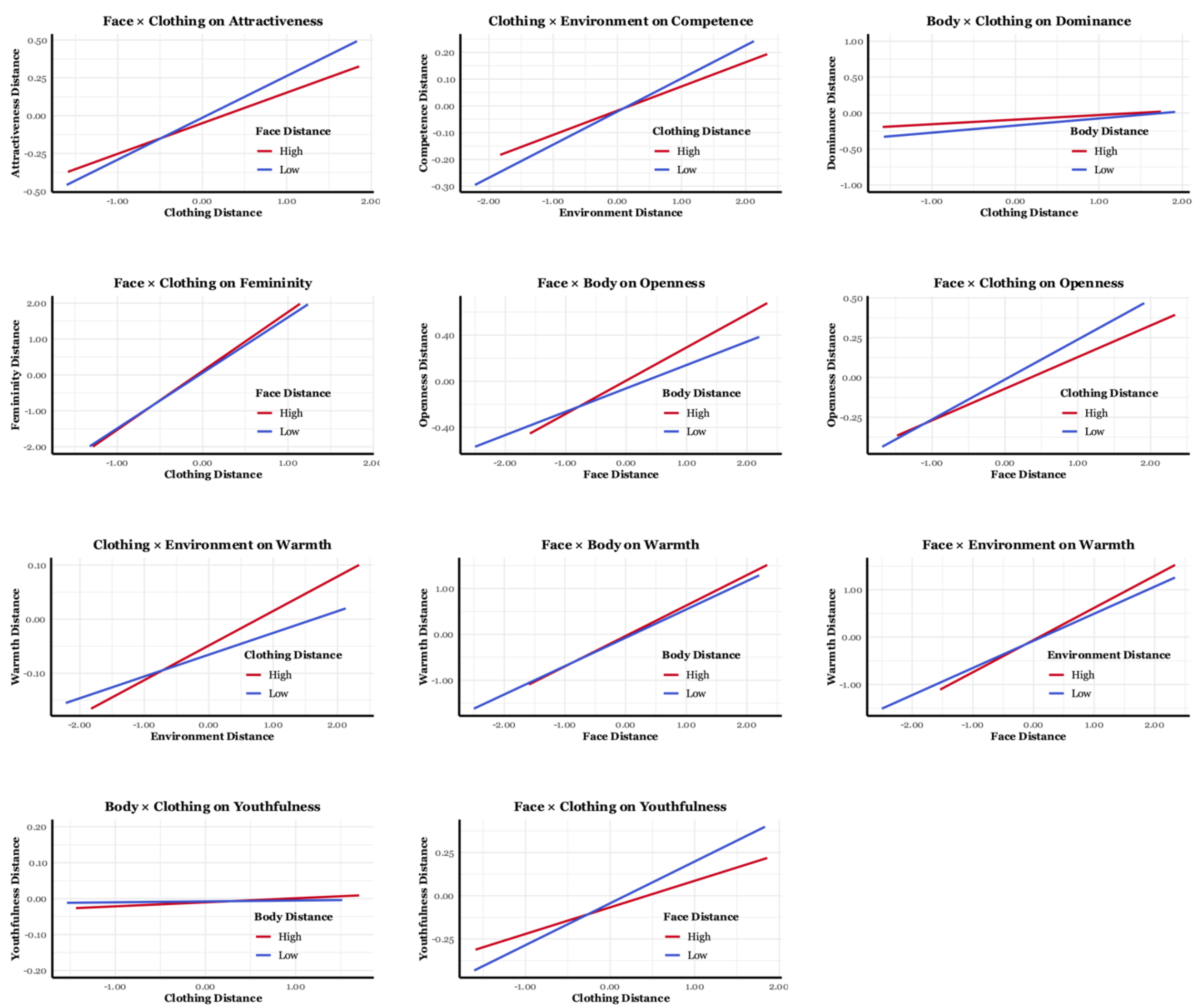


Fig. 6. Interactions between coarse-category cues on trait impressions. One model per trait regressing the distances in the trait impression on the distances in all four coarse-category cues and the distances in their two-way interactions were fitted using representational similarity

analysis with Ridge regression and cross-validation as pre-registered. Each panel plots a statistically significant interaction effect between two coarse-category cues on a trait impression (y-axes). To visualize these interaction effects, we split one of the cues into high distances (red lines), medium distance, and low distances (blue lines) and plotted for the high-distance and low-distance groups the Pearson correlations between the distances in another cue (x-axes) and the distances in a trait impression (y-axes).

Naturalistic Cues Causally Shaped Trait Impressions

Given the complex interactions we observed, it is necessary to test whether the predictions we found above indeed described the cues people used to form first impression in naturalistic contexts. To this end, we leveraged state-of-the-art artificial intelligence tools to manipulate one cue at a time realistically in a subset of the naturalistic images (see Materials and Methods; see examples in Table 3). In brief, we identified cue-trait pairs that i) diversified the coarse-category cues they belong to; ii) diversified the trait impressions predicted; iii) had unique explained variance; iv) had congruent effects between all features within the cue; and v) with available algorithms that manipulate the cue realistically without distorting other cues.

The above procedure identified two cue-trait pairs: facial expressions of emotions and perceived warmth, and clothing style and perceived attractiveness. To decide how to manipulate each feature belonging to the selected cues (expressions were rated on 8 emotions and clothing styles were rated on 4 features), we computed the univariate Pearson correlation between each feature and the target trait impression for female and male target individuals respectively. For both genders, positive facial expressions of emotions were positively correlated with perceived warmth (rs > 0.29, ps < .001) and negative facial expressions of emotions were negatively correlated with perceived warmth (rs < -0.61, ps < .001). For both genders, formal and provocative clothing styles were positively correlated with perceived attractiveness (rs > 0.10, ps < .011). For female targets, feminine clothing style was positively correlated with perceived attractiveness ($r = 0.40$, $p < .001$); for male targets, masculine clothing style was positively correlated with perceived attractiveness for male ($r = 0.13$, $p = .001$). Based on these results, we used OpenArt to manipulate the target person's facial expressions of emotion to be either happy or frowning. We used Adobe Firefly to manipulate clothing style to be either provocative, formal, and consistent with gender norms (feminine for females and masculine for males) or conservative, casual and inconsistent with gender norms (masculine for females and feminine for males).

We confirmed that these manipulations were successful (Fig. 7A-B). Target individuals with happy facial expressions of emotions were perceived as happier than those with frowning facial expressions (image-level paired t-test: $t(146) = 34.27$, $p = 1.07\text{e-}71$, 95% CI = [1.74, 1.95], $d = 1.97$; individual-level linear mixed modeling with images and participants as random effects: $\beta = 1.84$, $SE = 0.08$, $t(182.87) = 24.21$, $p = 6.29\text{e-}59$). Target individuals with provocative, formal, and gender-norm conforming clothing style were perceived as more provocative, feminine (for female targets) / masculine (for male targets), and formal than those with conservative, casual, and gender-norm nonconforming clothing style ($t(146) = 21.54$, $p = 3.56\text{e-}47$, 95% CI = [1.22, 1.47], $d = 1.67$; $\beta = 1.35$, $SE = 0.07$, $t(246.72) = 18.46$, $p = 2.25\text{e-}48$). These results indicate that we succeeded in manipulating specific cues in naturalistic images using AI tools.

Using these manipulated images, we found that people perceived the same target person as warmer when the person's facial expressions of emotion were manipulated to be happy than when the person's facial expressions of emotion were manipulated to be frowning (image-level paired t-test: $t(146) = 26.93$, $p = 1.71\text{e-}58$, 95% CI = [1.29, 1.50], $d = 1.83$; individual-level linear mixed modeling with images and participants as random effects: $\beta = 1.40$, $SE = 0.10$, $t(109.14) = 13.61$, $p = 2.88\text{e-}25$ for pilot Study 2a; $t(146) = 26.14$, $p = 6.11\text{e-}57$, 95% CI = [1.02, 1.19], $d = 1.68$; $\beta = 1.10$, $SE = 0.10$, $t(109.38) = 11.20$, $p = 7.55\text{e-}20$ for pre-registered Study 2b; Fig. 7C). People perceived the same target person as more attractive when the person's clothing style was manipulated to be more provocative, formal, and gender-norm conforming than when the person's clothing style was manipulated to be more conservative, casual, and gender-norm nonconforming ($t(146) = 6.53$, $p = 1.038\text{e-}09$, 95% CI = [0.12, 0.23], $d = 0.20$; $\beta = 0.18$, $SE = 0.03$, $t(85.44) = 6.18$, $p = 2.10\text{e-}08$ for Study 2a; $t(146) = 5.89$, $p = 2.50\text{e-}08$, 95% CI = [0.10, 0.21], $d = 0.17$; $\beta = 0.16$, $SE = 0.03$, $t(83.73) = 5.63$, $p = 2.39\text{e-}07$ for Study 2b). These results showed that people indeed use cues of facial expressions of emotions to form impressions of warmth and that they use cues of clothing style to form impressions of attractiveness.

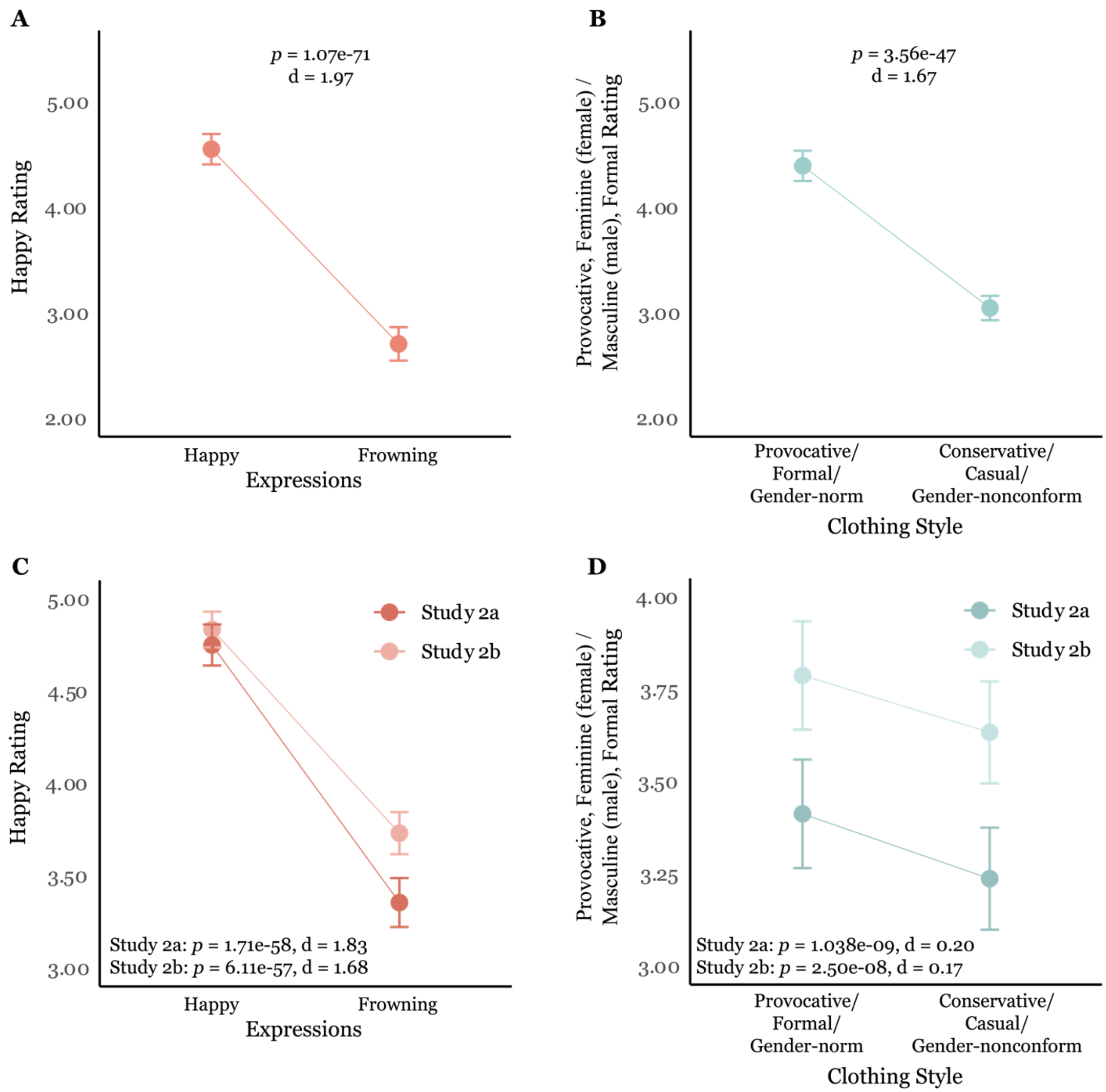


Fig. 7. Causal effects of naturalistic cues on trait impressions. (A) Manipulation checks for manipulated facial expressions of emotion (x-axis) on happy rating (y-axis) and (B) manipulated clothing style (x-axis) on clothing style rating (y-axis). (C) Causal effects of manipulated facial expressions of emotions (x-axis) on perceived warmth (y-axis) from naturalistic images across Studies 2a (pilot, darker color) and 2b (pre-registered, lighter color). Dots indicate the mean

ratings. Error bars indicate 95% confidence intervals. (D) Causal effects of manipulated clothing styles (x-axis) on perceived attractiveness (y-axis) in naturalistic images across Studies 2a & 2b.

Discussion

To advance an understanding of the mechanism underlying trait impressions in naturalistic contexts, here we investigated the roles of a comprehensive set of cues identified based on prior theories in trait impressions from a diverse set of naturalistic images (Fig. 1). To overcome the technical barriers to analyzing and manipulating naturalistic cues, we leveraged a range of novel computational tools to quantify rich cues (Fig. 2) to test the correlational effects between cues and impressions (Study 1) and manipulate individual cues to test the causal effects of cues on impressions (Study 2). Across two-preregistered studies, we found that trait impressions from naturalistic images showed high consensus across U.S. representative participants (Fig. 3A). Although many cues were proposed to be important to trait impressions in the literature (Table 1), only a small number of cues predicted trait impressions in naturalistic contexts (Figs. 3C & 4; Tables S1-S2). These predictive cues carried unique information for trait impressions that were not explainable by other available cues; they also carried information that was shared with at least some of the cues that were simultaneously present in the naturalistic context (Fig. 5; Tables S3-S4). Complex interactions between cues were found, with some between predictive cues and nonpredictive cues (Figs. 6 & S1; Tables S5-S6). Given the shared variances and interactions between cues, it was necessary to test whether people indeed used the information found predictive in the correlational analyses. We manipulated a subset of cues in the naturalistic images and showed that the predictions were indeed causal (Fig. 7). Together, these findings advance a mechanistic understanding of how people use different information to form trait impressions in naturalistic contexts.

Given the much more complex information in naturalistic images and the various ways that each information stream could be interpreted, the trait impressions people form from naturalistic images may be more variable than those from controlled stimuli (*18*, *57*, *60*). Nevertheless, we found high consensus in the impressions of all seven traits among a diverse group of participants that were representative of the age, gender, and race distributions of the U.S. population (Fig. 3A). These findings suggest that the shared experiences and cultural norms within a society may have a greater impacts than individual differences on shaping the way people interpret rich social cues and map different social cues to individual dispositions (*64*, *65*).

In sharp contrast to the conclusions from prior literature, only a very small number of the 16 cues previously identified as relevant to trait impressions predicted impressions in our study (Fig. 4). Using only a sparse set of cues likely facilitates rapid trait impressions given the immense amount of social information in naturalistic context. This is consistent with the phenomenon found in physical perception where people often attend to only a limited set of important cues (*31*–*34*). Specifically, we found that people only relied on appearance cues such as facial structure, clothing style, and hair cues to infer physical-related traits such as femininity, youthfulness, and attractiveness. For approachability-related traits such as warmth and openness, people relied on cues about valence, such as facial expressions of emotions and environmental vibe. When inferring ability-related traits such as dominance and competence, people relied on behavioral cues, such as actions. Our finding suggests that prior work constraining perceivers to cues presented in an unnaturalistic way may have missed the important of those cues in more naturalistic contexts.

It remains an open question how people come to decide which cues are important and should attend to for different trait impressions. Our findings suggest that important cues for a specific trait impression tend to carry unique information that cannot be explained by other cues (Fig. 5). Note that unique information does not necessarily mean that it is inconsistent with the information from other cues. In fact, we also found that predictive cues also convey information that is shared with some of the other available cues (Fig. 5). These findings suggest that social cues in naturalistic contexts tend to be redundant and that only a small subset of cues carry unique information requires people's attention (*66*, *67*). People may have learned to decide the importance of different social cues based on the relationship between the information conveyed in these cues in daily life. However, there may be other (non-mutually exclusive) mechanisms driving the determination of important cues. For instance, the important cues may be more valid for the inferences of a specific trait, or that they may simply co-occur with certain traits more often without any true causal relation, which remains to be tested in future research.

The limited set of information people tend to use for forming trait impressions in naturalist contexts may also explain the general high correlations between different trait impressions (Fig. 3B). Although people have hundreds of different words for describing the traits of other people, prior work has shown that all these trait impressions are highly correlated and can be summarized by only a small number of dimensions, such as the four dimensions of warmth, competence, femininity, and youthfulness (*56*, *57*, *68*). The limited set of cues people use may constrain the limited variability in the trait impressions that they form through a bottom-up mechanism. However, this does not preclude the greater variability in trait impressions that could be introduced by top-down mechanisms such as conceptual knowledge, stereotypes, cultural norms, and language (*64*, *69*, *70*).

On the other hand, our results suggest that the many cues proposed to be important in prior theories could still play a role in shaping trait impressions even though they do not offer significant prediction on their own. We found many significant interaction effects between a predictive cue and a nonpredictive cue, suggesting that a nonpredictive cue could shape impressions indirectly through shaping how much a predictive cue is utilized (Fig. 6; Tables S5-S6). For instance, perceived attractiveness was significantly and independently predicted by clothing style, hair color, and hair style (Fig. 4); however, we found significant interactions between clothing style and body shape ($\beta = 0.014$, 95%CI = [0.003, 0.039]) and between clothing style and body pose ($\beta = -0.015$, 95%CI = [-0.042, -0.005]). These findings suggest that depending on the specific body shape and body pose, people may use clothing style cues to a different degree to form impressions of attractiveness.

The complex interactions between cues in naturalistic contexts is one of the reasons why many researchers prefer to investigate each cue in isolation. However, here we showed that even in naturalistic contexts, researchers can evaluate the effect of each cue at a time. Using novel artificial intelligence tools, we successfully manipulated facial expressions of emotions and clothing styles of the target individuals realistically in the original naturalistic images. We showed that both cues causally changed the impressions people form of the targets (Fig. 7). Tools like these that allow for the integration between controlled experiments and naturalistic contexts hold great potential for advancing a more ecologically valid understanding of social perception.

Several limitations constrained the conclusions from our research. First, although we tried to use state-of-the-art computational tools to quantify as many cues that were proposed to be important by prior thoeries as possible, many of the cues had to be quantified by human participants due to poor algorithm performance. These human quantifications were based on the features defined by ourselves (e.g., which emotions we decided to include for the facial expression cue). The subjective selection of these features for each cue was based on prior literature (Table 1) but may still have biased the results. However, note that the predictions were not constrained to whether the cues were computationally quantified or human quantified. Both types of cues were found predictive for different trait impressions (Fig. 4). Second, although we investigated the mechanism of how different cues interacted to shape impressions, we only considered linear two-way interaction effects. Our results did not capture the potential interactions between three and more cues nor the interactions that are nonlinear. Third, we tested the causal effects of specific cues in naturalistic images beyond establishing correlational findings. However, due to technical limitations, we were not able to test the causal effects of a wider range of cues, such as actions. We tested many artificial intelligence tools for the manipulation of actions, which all failed to deliver realistic manipulation without distorting other cues. The causal effects we established here may not generalize to other cue-trait pairs. Finally, we attempt to advance a more naturalistic understanding of trait impressions by investigating judgments of a diverse set of naturalistic images. Forming impressions from naturalistic images is ubiquitous in daily life (e.g., scrolling through social media posts), but our conclusions may not generalize to other naturalistic contexts such as face-to-face interactions.

Despite these limitations, our research provides a much more comprehensive characterization of the information determinants of trait impressions than existing work. Our findings provide novel insights into what information is used in naturalistic contexts and why. The computational pipeline we offer here also opens new doors for combining the strengths of naturalistic designs and controlled experiments for advancing a more ecologically valid understanding of social cognition.

Materials and Methods

Study 1

Participants

Participants of Study 1 were recruited from Cloud Research Connect. We recruited participants who satisfied the following criteria: fluent in English, located in the United States, aged 18 and older, with normal or corrected-to-normal vision, and educational attainment of high school or above.

To determine the sample size, we did formal power analyses using two distinct methods. Since all analyses were performed on a group level across participants, we were mostly concerned about the reliability of the data at a group-level. Therefore, the power analyses targeted two types of group-level data reliability: i) the consensus between perceivers, and ii) the stability of average ratings across perceivers. First, given the naturalistic nature of our designs, we based our power analysis on a prior study that investigated the continuous ratings of trait impressions during naturalistic video viewing (*18*). We computed the between-participant consensus in their trait ratings, which resulted in a standardized Cronbach alpha of 0.488 per trait on average. Applying the Spearman-Brown prediction formula and aiming for a standardized Cronbach alpha of at least 0.7 (threshold for good reliability according to convention), the results indicated that we need at least 40 participants per trait to achieve the targeted between-perceiver consensus. Second, according to (*71*), which examined ratings of a wide range of traits and emotions from naturalistic images, a stable average rating (for a stability corridor of 0.5) can be achieved with 42 participants for all of their examined traits and emotions. This method suggested that 42 participants should be a sufficient sample size for achieving a good consensus between participants for a wide range of social judgments in a naturalistic context. Therefore, we planned to have ratings from at least 42 participants for each image for both trait ratings (Study 1a) and cue annotations from human participants (Study 1b). To ensure that we measure initial trait impressions without the influence of familiarity, participants who have rated one trait in trait rating experiments were not eligible to rate other traits but were still eligible to rate at most one cue in the annotation experiment for a subset of images that they had not been exposed to in trait rating experiments.

For both Study 1a (trait ratings) and Study 1b (cue annotations), trials were excluded if the response times were shorter than 200ms or longer than 10000ms. Participants were excluded if they a) were subject to trial-wise exclusion for more than 10% of the trials, or b) had more than one error in the attention check, or c) gave all images in a block the same rating.

Based on these exclusion criteria, for Study 1a (trait ratings), 85 participants of the 990 participants who initially participated were excluded (8.59%), resulting in a final set of 905 participants, satisfying the planned sample size (i.e., at least 42 participants rated each image). The remaining participants were representative of the United States population demographics: 434 men, 460 women, and 11 non-binaries; age ranged from 18 to 81 ($M = 44.47$, $SD = 15.70$), 24% aged 18-29, 26% aged 30-44, 27% aged 45-59, 23% aged 60-81; 729 White, 104 Black, 63 Asian, and 9 others. For Study 1b (cue annotations), 38 participants of the 1,568 participants who initially participated were excluded (2.42%), resulting in a final set of 1,530 participants, satisfying the planned sample size. The remaining participants were representative of the United States population demographics: 820 men, 694 women, and 16 non-binaries; age ranged from 18 to 83 ($M = 44.82$, $SD = 15.48$), 22% aged 18-29, 28% aged 30-44, 25% aged 45-59, 25% aged 60-81; 1256 White, 183 Black, 80 Asian, and 11 others (see Table 2 for more details).

Table 2. Participant Characteristics across Studies 1 & 2

Study	Power Analysis	Pre-registered Recruitment Plan	Total	Exclude	Final	Gender	Age	Race
Study 1a Trait Rating Experiment	$N \geq 40$ across 1125 images for each trait	$N \geq 42$ across 1125 images for each trait	990	8.59%	905	460 (48%) Women 434 (51%) Men 11 (1%) Non-binaries	Min = 18 Max = 81 M = 44.47 SD = 15.70 215 (24%) Aged 18-29 239 (26%) Aged 30-44 244 (27%) Aged 45-59 207 (23%) Aged 60-81	729 (81%) White 104 (11%) Black 63 (7%) Asian 9 (1%) Others
Study 1b Cue Annotation Experiment	$N \geq 40$ across 1125 images for each cue	$N \geq 42$ across 1125 images for each cue	1568	2.42%	1530	820 (54%) Women 694 (45%) Men 16 (1%) Non-binaries	Min = 18 Max = 83 M = 44.92 SD = 15.48 331 (22%) Aged 18-29 427 (28%) Aged 30-44 390 (25%) Aged 45-59 382 (25%) Aged 60-81	1256 (82%) White 183 (12%) Black 80 (5%) Asian 11 (1%) Others
Study 2 Manipulation check	$N_{images} \geq 42$	$N \geq 42$ across 147 images for each cue	270	7.41%	250	125 (50%) Women 123 (49%) Men 2 (1%) Non-binaries	Min = 19 Max = 78 M = 37.43 SD = 11.46 72 (29%) Aged 18-29 120 (48%) Aged 30-44 45 (18%) Aged 45-59 13 (5%) Aged 60-81	176 (70%) White 37 (15%) Black 28 (11%) Asian 9 (4%) Others

Study 2a Pilot Study	$N_{images} \geq$ 42	N ≥ 42 across 147 images for each cue	161	8.70%	147	83 (56%) Women 63 (43%) Men 1 (1%) Non-binaries	Min = 20 Max = 66 M = 35.95 SD = 8.55 27 (18%) Aged 18-29 102 (69%) Aged 30-44 17 (12%) Aged 45-59 1 (1%) Aged 60-81	123 (84%) White 13 (9%) Black 11 (7%) Asian 0 (0%) Others
Study 2b Preregistered Replication	$N_{images} \geq$ 42	N ≥ 42 across 147 images for each cue	185	7.03%	172	85 (49%) Women 84 (49%) Men 3 (2%) Non-binaries	Min = 18 Max = 69 M = 35.97 SD = 9.98 49 (28%) Aged 18-29 94 (55%) Aged 30-44 26 (15%) Aged 45-59 3 (2%) Aged 60-81	139 (81%) White 22 (13%) Black 10 (6%) Asian 1 (1%) Others

Note: All survey questions were voluntary. Non-responses were omitted.

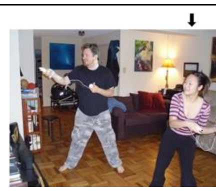
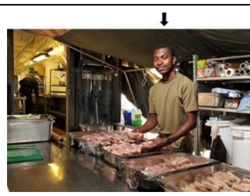
Materials

The stimuli we used in the present study were selected from the EMOTIC (EMOTIons in Context) dataset (*72*) and the AHP (Amodal Human Perception) dataset (*73*). The EMOTIC dataset consists of 23,571 naturalistic images with 34,320 annotated people in real-life environments, annotated with their apparent emotions across an extended list of 26 categories. The AHP dataset consists of 56,599 naturalistic images with people in real-life environments. The advantage of these two datasets is that they include a large number of photos of people in a wide range of everyday life contexts (e.g., walking down the street, hanging out with friends, working, exercising, cooking, etc.)

To ensure that the target person in the images can be seen and annotated and are ethical to ask about impressions of them, we excluded the images a) with child and teenager as the target person, b) where the face or upper body is not visible, i.e., less than half of the face or body shown, c) with occlusion (different person's body/face overlap in the sense that we cannot crop the important parts of body/face of the target person without part of the other person, with sunglasses, with mask, face/half body overlapping with other objects that block important features of the face or body), d) with blurry face/body (e.g., pixelated), e) with overexposed or underexposed faces or bodies, f) in black and white, g) with text on person, h) of too private scenes (e.g., bathroom, nudity), i) where using an arrow cannot unambiguously indicate the target person, j) which are selfies, or k) with heavily edited artifacts.

We identified all images and all individuals in the images that survived the above exclusion criteria. We indicated the target person in each image by adding a black arrow on top of the image (all images are padded on the top so that the arrow appears outside of the original image). Our final set of stimuli contained 1,031 unique images with 1,125 unique target persons (i.e., 1,125 experiment images, each indicating a unique target person). These target persons were of diverse combinations of race, gender, and age (see Table 3 for demographic distribution).

Table 3. Naturalistic Stimuli Characteristic across Studies 1 & 2.

Sources	Example Images	Experiment Images	Gender	Age	Race
Study 1 EMOTIC: EMOTions In Context Dataset (Kosti et al., 2019)	 	 	535 (48%) Women 590 (52%) Men	632 (56%) Aged 18-29 198 (18%) Aged 30-44 192 (17%) Aged 45-59 103 (9%) Aged over 60	857 (76%) White 63 (6%) Black 158 (14%) Asian 47 (4%) Others
Study 1 AHP: Amodal Human Perception dataset (Zhou et al., 2021)	 	 			
Total Number	1125				
Study 2 Images manipulated for Emotion In perceived Warmth		 	71 (48%) Women 76 (52%) Men	81 (55%) Aged 18-29 33 (22%) Aged 30-44 25 (17%) Aged 45-59 8 (5%) Aged over 60	115 (78%) White 10 (7%) Black 22 (15%) Asian

		 			
Study 2 Images manipulated for Clothing Style in perceived Attractiveness	 	   	71 (48%) Women 76 (52%) Men	80 (54%) Aged 18-29 33 (22%) Aged 30-44 25 (17%) Aged 45-59 9 (6%) Aged over 60	115 (78%) White 10 (7%) Black 22 (15%) Asian
Total Number	147				

Note: A black arrow indicating the target person was added to each image to use in the study.

Cue Quantifications

We identified a comprehensive set of 16 fine-grained across 4 coarse-category cues that were found important to trait impressions in prior research. Nine of the fine-grained cues were quantified using a wide range of computational tools (face: facial structure; body: gaze direction, action, head pose, body pose, body shape; clothing: clothing color; environment: environment color and gist), Specifically, we used the Python toolbox Py-Feat (*74*) to quantify facial structure (512 features) provided by an algorithm that is trained to distinguish one facial identity from another. We also used Py-Feat to quantify head poses (3 features: pitch, roll, and yaw). We used Part Attention Regressor (PARE) (*75*) to quantify body shapes (10 features) and body poses (93 joint distance features). We used OpenCV (*76*) to quantify the color distribution of clothing and environment in the LAB color space (L: lightness, A: red-green, B: blue-yellow). We used the mean value of L, A, and B features across all the relative pixels to represent color distribution. We used state-of-the-art vision models and natural language processing models provided by OpenAI (*77*) to annotate high-level visual cues: action and gist. Specifically, we first used vision models to identify the actions of target person (what the person is doing) and the environment gist for each image (abstract description of the environment), described using words; we then quantified these verbal contents using natural language processing models (1,536 features). We also used the visual model to categorize gaze direction as frontal, left, right, up, down, or closed eyes and represented it as dummy variables.

Cues that cannot be accurately annotated by existing computational algorithms were rated by humans. For hair color, since its perception is relatively objective, hair color was rated by four researchers on a 3-point Likert scale for 5 feature (black, blond, brown, red, and white). Facial expressions of emotion was rated on 8 features: anger, aversion, disconnection, esteem, fear, happiness, sadness, surprise (six basic emotions and two emotions sampled from a recent work (*78*). Skin color was rated based on 10 different color samples from light to dark that resemble the natural distribution of human skin color (*79*). Clothing style was rated on 4 features, respectively (formal, provocative, feminine, and masculine). Hair style was rated on 3 features, respectively (half participants rated formal, provocative, and feminine, another half rated formal, provocative, and masculine). Environment complexity was rated on 2 features (number of elements, organization of elements). Environment vibe was rated on 2 features (threat/non-threat, positive/negative).

Procedures

In Study 1a (trait ratings), each participant was assigned to rate a randomly selected one-third of all the images. Participants viewed the assigned images one by one in random order and rated the target person indicated by the arrow on only one of the seven traits. In each trial, participants first saw a fixation for 500 ms to 1000 ms, and then they saw the image with the target person and provided ratings using a 7-point Likert scale (Fig. 8). After providing trait ratings for all images, participants completed a questionnaire about their understanding of the trait that they were asked to rate and demographic information.

In Study 1b (cue annotations), each participant rated a random subset of images (that they had not seen before if the participant happened to have participated in Study 1a for rating traits). The number of images ensured that the task length was reasonable. Participants viewed a random subset of the images one by one in random order and rated the image on all features of a given cue (e.g., if the given cue is facial expressions of emotions, then they rated each target person on all the 8 emotions one by one in random order). Participants provided ratings using a 7-point Likert scale (10-point scale for skin color).

To ensure data quality, in 1.5% of the trials in Studies 1a and 1b (no fewer than 4 trials), there were attention checks. Specifically, we randomly choose 1.5% of the images that contained more than one available target persons (e.g., one original image may have two or more different target persons that satisfied our exclusion criteria, generating multiple experiment images with distinct target persons). In each attention check trial, participants saw two images side by side, depicting the same original image but different target persons as indicated by the arrows. Participants were asked which target they had rated in the preceding trial. For Study 2b cue annotations about nontarget-person related cues (i.e., environmental cues), the attention checks asked which environment (with the target person cropped out) between two images that were highly similar in environmental gist (sampled based on gist features) the participants saw in the last trial.

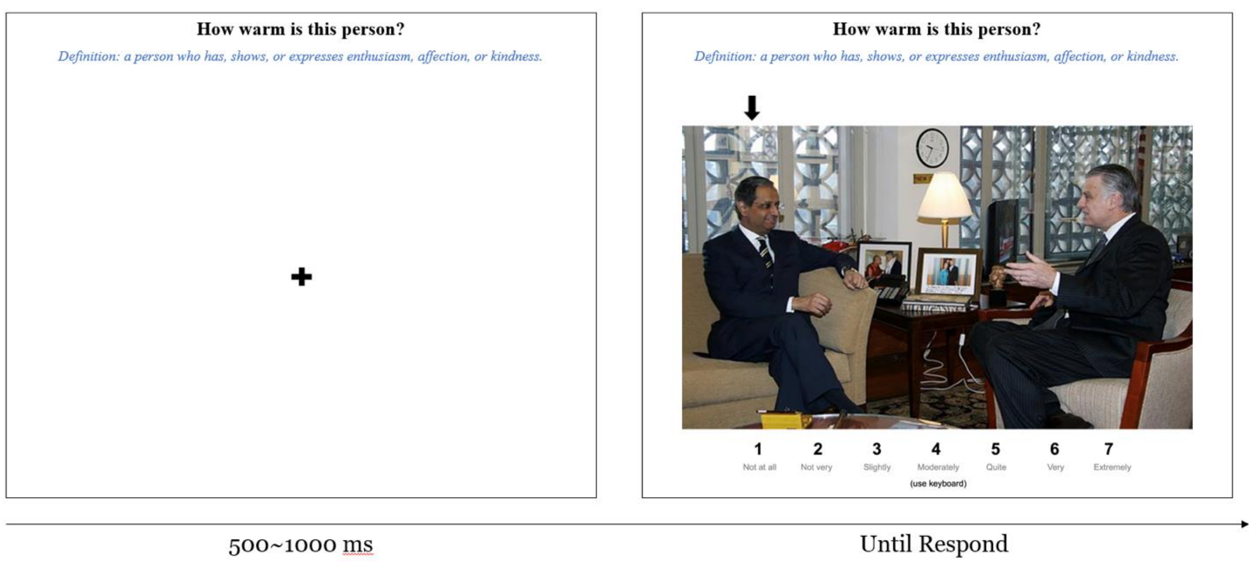


Fig. 8. Experiment paradigms for Study 1a. Participants rated a given target person indicated by the black arrow in a naturalistic image on a given trait. Similar procedure was used for Study 1b (cue annotations) except that the questions asked on top of the screen differed.

Analysis Methods

Consensus. We computed the split-half consensus of trait judgments in naturalistic contexts. For each trait, we split all participants into arbitrary halves to compute the Pearson correlation between the aggregate ratings averaged across the split halves and applied the Spearman-Brown formula to correct for the average split-half correlation.

Principal Component Analysis. As most computational algorithms return uninterpretable features, we performed principal component analysis (PCA) on the quantified features per cue to evaluate how well the PCs capture the variation in a given cue across our naturalistic images.

Representational Similarity Analysis. To test whether similarity in cues predicted similarity in trait impressions, we used representational similarity analysis (RSA). RSA allows for comparing different high-dimensional measures (e.g., trait ratings, visual cues) of the same set of items (e.g., images). To increase out-of-sample generalizability and alleviate the problem of collinearity between cues, we combined the RSA analysis with Ridge regression with cross-validation (Fig 9A). For each trait, we first computed the average trait rating per image across participants. We then calculated two matrices that represent the relations between every pair of images based on two different measures: one based on the trait ratings – we calculated the Euclidean distance between two images' the aggregate trait ratings; the other based on the visual cues – we calculated the Euclidean distance or Cosine distance (for action and gist, as they used word embeddings) between two images' quantified visual cues. In particular, we computed one distance matrix per fine-grained cue across all its relevant features. For instance, the fine-grained cue of facial structure was measured using 512 features, so we computed the distance between every pair of images along their vectors of the 512 features, resulting in one distance value for facial structure between a pair of images. We used these trait distances as the dependent variable and cue distances as independent variables in Ridge regressions.

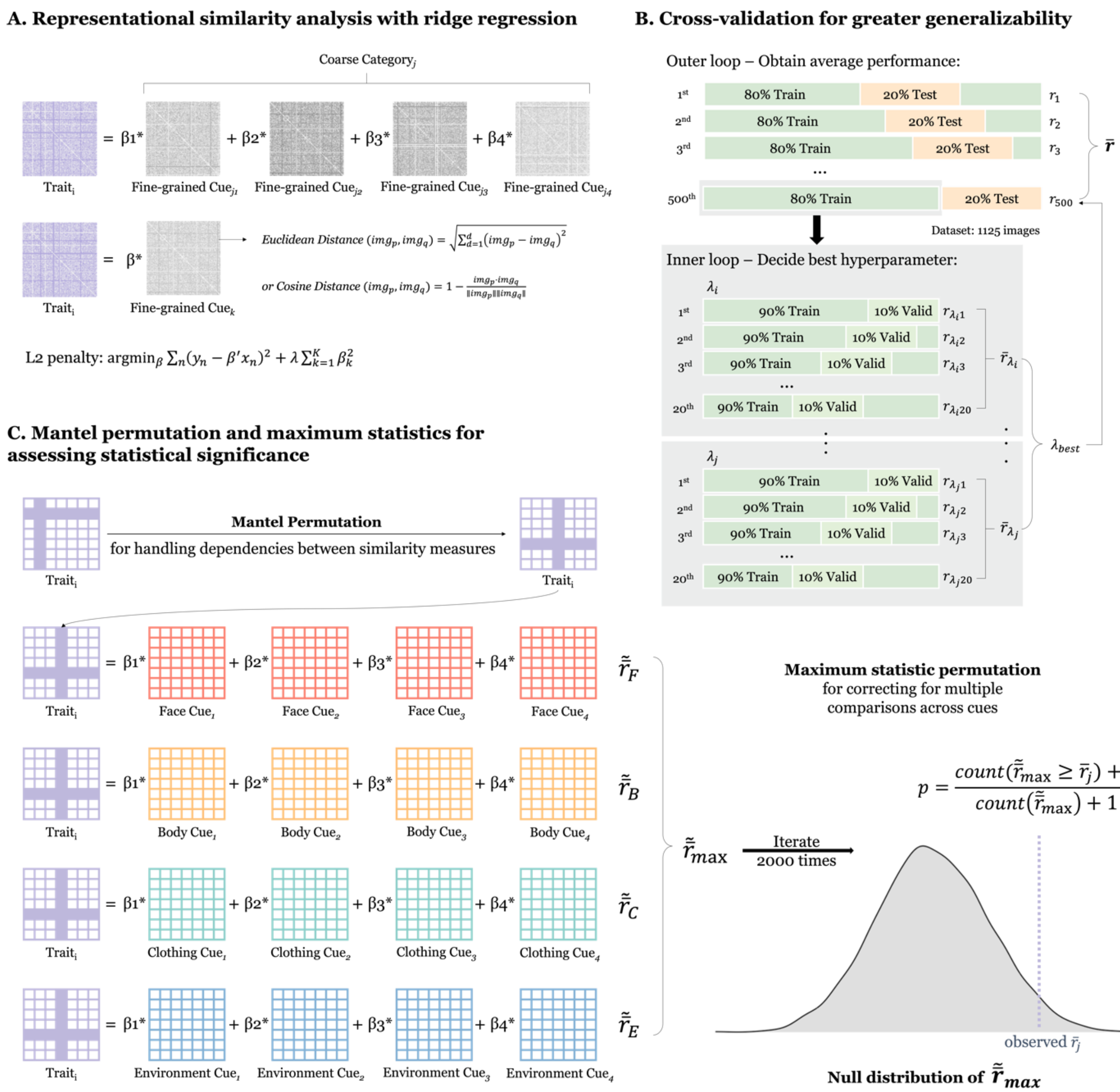


Fig. 9. Cue prediction analysis pipeline. (A) Representational similarity analysis with ridge regression. Representational similarity analysis compares the distance between two images based on their trait ratings with the distance between them based on cues (only the unique elements in the lower triangle of the matrices are used). Ridge regression helps reduce overfitting to data and alleviate the problem of collinearity between cues. We combine these two analyses to estimate

the prediction of each cue (each coarse-category cue or each fine-grained cue) for each trait. (B) Cross-validation procedures for ridge regression. Five hundred outer loops splitting the data into train and test are used to increase generalizability. Twenty inner loops splitting the outer-train data into inner-train and validation data are used in automatically determining the optimal regularization hyperparameter. (C) Mantel permutation and maximum statistics for significance testing and multiple comparison correction. Elements in the representational similarity matrix are not independent and thus their unique elements in the lower triangle cannot just be randomly permuted and instead need to be permuted using the Mantel permutation procedure. To correct for multiple comparisons across the cues in each of our pre-registered analyses while considering the interdependence between the cues, we used the maximal statistic permutation procedure.

Ridge Regression for Cue Prediction Analysis. To test the individual contributions of coarse-category cues, we regressed trait distances on the cue distances of all four fine-grained cues that belong to each coarse-category cue for each trait, using Ridge regression with nested cross-validation (Figs. 9A & 9B). We randomly split 80% of the images for training and 20% of the images for testing in each cross-validation iteration (outer iteration) 500 times. Within each outer iteration, we randomly split the training images further into 90% of the images for training and 10% of the images 20 times for validation (inner iteration) to select the optimal regularization hyperparameter λ. We computed the trait distances and cue distances based on the image pairs within each training, validation, and test set. We then standardized the training set and the test set using the mean and standard deviation of the training set for both trait distances and cue distances to prevent data leakage. A similar standardization procedure was applied to the inner training and validation set. Once the optimal hyperparameter was selected across all inner iterations for a given outer iteration, we then used all training data in the outer iteration and the optimal λ to fit the model. Using the fitted model, we predicted the trait distances from the cue distances in the test set. Finally, we assessed how well the predictions matched the actual observed trait distances in the test set by calculating the Pearson correlation between the predicted values and the observed values in the test set. After looping over all outer iterations, we averaged these correlations across all outer iterations, obtaining an average prediction accuracy, $\bar{r}$, per trait per coarse-category cue.

To test the significance of model prediction accuracies for each coarse-category cue and compare face cue with other coarse-category cues, we used the Mantel permutation procedure to permutate the trait distance matrix and used the maximum statistic permutation test to correct for multiple comparisons across cues or cue pairs (Fig. 9C). In each permutation iteration, we shuffled the trait distances using the Mantel permutation procedure, which respects the independency between datapoints in the matrix. We then refitted the model using these shuffled values as the new dependent variable to obtain a new prediction accuracy for each coarse-category cue, $\bar{\bar{r}}$, and the difference in prediction accuracy between face cue and other coarse-category cues, $\Delta|\bar{\bar{r}}|$. Then we identified the maximal absolute $\bar{\bar{r}}$ across cues and its sign (negative $\bar{\bar{r}}$ is meaningful in our case as an indication of predicting the antonym of a trait) and maximal $\Delta|\bar{\bar{r}}|$ across cue comparisons to generate a null distribution of the signed maximal statistic across permutation iterations. Based on the respective null distribution, we calculated the significance of the observed prediction accuracy for each coarse-category cue and each comparison between face cue and another coarse-category cue.

To test the univariate contributions of each fine-grained cue, we used the same statistical technique as described above, but the independent variables were each of the fine-grained cue distances instead of all fine-grained cue distances that belong to a given coarse-category cue.

Variance Partition Analysis. To test the unique and common contributions of each coarse-category cue, we used the statistical technique of variance partition analysis (Fig. 10A).

We fit three models for each tested cue using Ridge regression with nested cross-validation. We only tested the coarse-category cues that have significant univariate contribution. For each target coarse-category cue, we regressed the trait distances on the cue distances in three models, i) full model: regressing trait distances on the fine-grained cue distances of all coarse-category cues, ii) target cue model: regressing trait distances on the fine-grained cue distances for a given coarse-category cue, iii) left-one-cue-out model: regressing the trait distances on fine-grained cue distances of all but one left-out coarse-category cue. For each model, we computed a prediction accuracy $\bar{r}$ as mentioned above, and its explained variance, $sign(|\bar{r}|) * |\bar{r}|$. We calculated the unique contribution of a target coarse-category cue by subtracting the signed $|\bar{r}|^2$of the left-one-cue-out model from the signed $|\bar{r}|^2$of the full model. The common contribution of a given coarse-category cue with all other coarse-category cues was calculated by subtracting the signed $|\bar{r}|^2$of the full model from the sum of signed $|\bar{r}|^2$ between a certain target cue model and a corresponding left-one-cue-out model. The significance of the unique and common contribution of each coarse-category cue was assessed and corrected for multiple comparisons using Mantel permutation and maximal statistic permutation tests as mentioned above.

To test the unique and common contributions of each fine-grained cue, we used the same statistical technique, but each target cue was a fine-grained cue. Similarly, we focused on the fine-grained cues that had a significant contribution. For each target fine-grained cue, we also fit three models, respectively: i) full model: regressing trait distances on all the fine-grained cue distances, ii) target cue model: regressing trait distances on the target fine-grained cue distances, iii) left-one-cue-out model: regressing the trait distances on fine-grained cue distances of all but one left-out fine-grained cue. We computed the unique contribution of each target fine-grained cue and its common contribution with other fine-grained cues and tested for their statistical significance using a similar method as described for the coarse-category cues above.

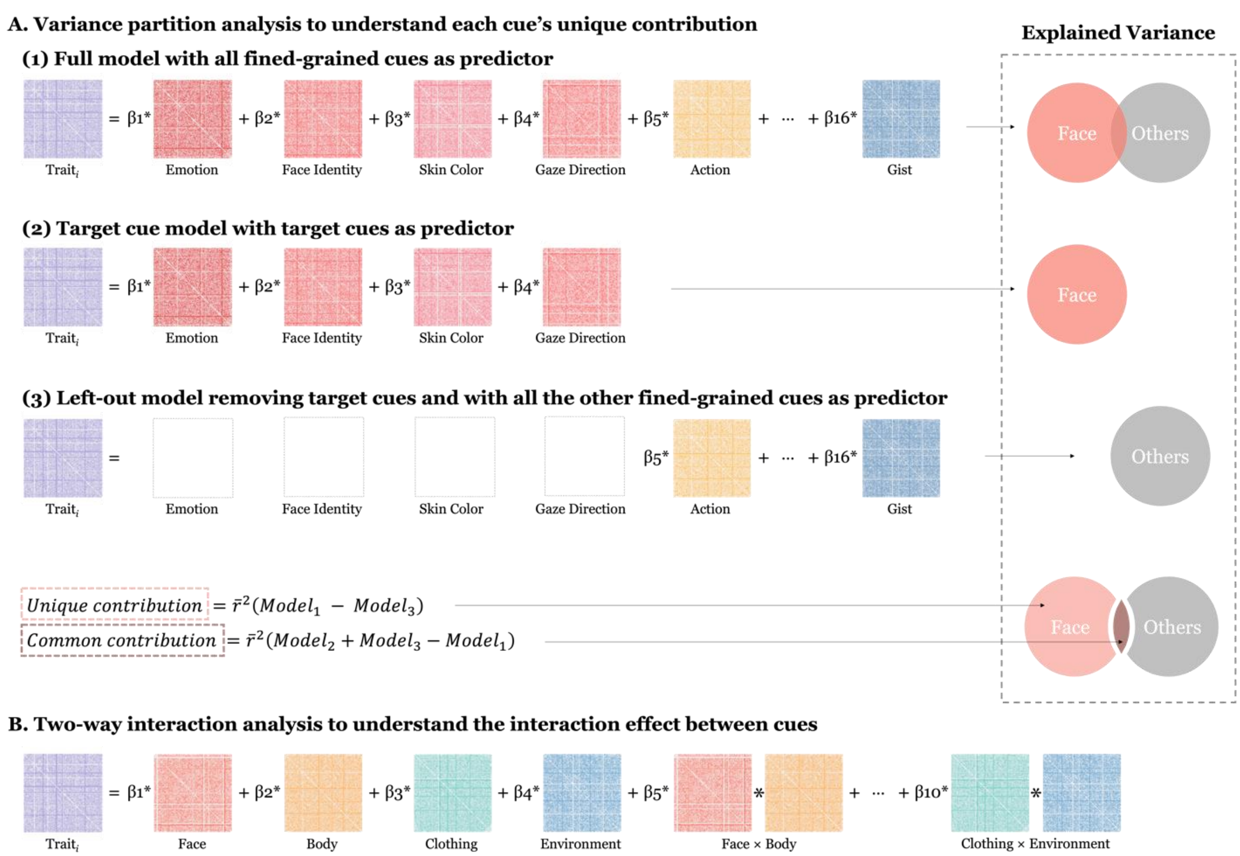


Fig. 10. Variance partition analysis and two-way interaction analysis. (A) Variance partition analysis for identifying the unique and common contribution of each cue compared to the rest of the cues. Three models were fitted for each cue (left formulas) with its variance explained indicated (right circles). (B) Representational similarity analysis with Ridge regression for testing two-way interactions.

Two-way Interactions between Cues. To test the interaction between different coarse-category cues, we started with two-way interactions (Fig. 10B). We regressed the trait distances on the coarse-category cue distances (combine all four fine-grained cues within a coarse-category cue to calculate one matrix for a coarse-category cue) and all the two-way interactions between the coarse-category cues, using Ridge regression with nested cross-validation. We assessed the significance of the coefficients of the interaction terms using the bootstrap procedure with 2000 iterations. We also tested the two-way interaction between different fine-grained cues, regressing the trait distances on the fine-grained cue distances and all the two-way interactions between the fine-grained cues, using Ridge regression with nested cross-validation.

Study 2

Participants

Participants of Study 2 were recruited from the same online research platform according to the same inclusion criteria as in Study 1. Based on the same sample size analysis as in Study 1, we planned to recruit 42 participants to rate each image for the manipulation check and Study 2a pilot study. Since each participant can only view and rate one version of the manipulated images, we planned to recruit 84 participants for the facial expressions of emotion manipulation check, pilot study for the effect of facial expressions of emotion manipulation, and the pilot study for the effect of clothing style manipulation. Since the manipulation check for clothing style manipulation needed to be performed for each gender separately, we planned to recruit a total of 168 participants.

For the pre-registered replication Study 2b, we also considered an exclusion rate of 5%, resulting in a planned sample size of 45 participants for rating each image, with a total of 180 participants across both cue-trait pairs. If an image were rated by fewer than 42 participants post-data exclusion, we continued data collection until all images had ratings from at least 42 participants. Participants who had completed our prior Study 1a or 1b, Study 2 manipulation check, or pilot Study 2a were not eligible for the preregistered Study 2b.

In both Study 2 manipulation check and experiments, participants rated the target persons one by one for a given facial expressions of emotion, clothing style, or trait. Trial-wise exclusion was done if a participant has a response time shorter than 200ms or longer than 10000ms for a trial. Participant-wise exclusion was done if a participant a) is subject to trial-wise exclusion for more than 15% of the trials, b) has more than one error in the attention check.

For manipulation check, after these exclusion criteria, 5 participants of the 88 participants who initially participated were excluded (5.68%), resulting 83 participants for manipulated facial expressions of emotion (43 men, 40 women, age ranged from 21 to 67: M = 38.89, SD = 10.76). Fifteen participants of the 182 participants who initially participated were excluded (8.24%), resulting 167 participants for manipulated clothing style (80 men, 85 women, 2 non-binaries, age ranged from 19 to 78: M = 36.71, SD = 11.75; see details in Table 2).

For pilot Study 2a, 8 participants of the 83 participants who initially participated were excluded (9.64%), resulting 75 participants for expressions-warmth pair (37 men, 37 women, 1 non-binaries, age ranged from 20 to 66: M = 36.84, SD = 9.50). Six participants of the 78 participants who initially participated were excluded (7.69%), resulting 72 participants for clothing style -attractiveness pair (26 men, 46 women, age ranged from 20 to 54: M = 35.01, SD = 7.39; see details in Table 2).

For preregistered Study 2b, 8 participants of the 95 participants who initially participated were excluded (8.42%), resulting 87 participants for expressions-warmth pair (44 men, 42 women, 1 non-binaries, age ranged from 18 to 69: M = 36.32, SD = 10.34). Five participants of the 90 participants who initially participated were excluded (5.56%), resulting 85 participants for clothing style -attractiveness pair (40 men, 43 women, 2 non-binaries, age ranged from 20 to 60: M = 35.61, SD = 9.65; see details in Table 2).

Materials

Power analysis indicated that 147 images were needed to detect a small effect size using an image-level paired t-test (d = 0.3, alpha = .05, power = .95). To maximize the diversity of the images that we manipulate, we applied maximum variation sampling procedure to systematically select the most representative 147 images along the 16 cues (most distinct from one another based on their cue quantifications) that can be successfully manipulated from the 1,125 images in Study 1 (see Table 3 for examples).

For expressions-warmth pair, we used OpenArt to manipulate the target person's facial expressions of emotion to either happy or frowning. For clothing style - attractiveness pair, we used Adobe Firefly to manipulate clothing style to either provocative, formal, and gender-norm conforming, or conservative, casual, and gender-norm non-conforming.

Procedures

We first conducted a manipulation check. For the facial expressions of emotion manipulation check, participants were randomly presented with one version of each of the 147 images and rated how happy the target person looks on a 7-point Likert scale. For the clothing style manipulation check, participants were assigned images of either male or female target persons. They rated how provocative, feminine, and formal the clothing looked for female target persons, or how provocative, masculine, and formal the clothing looked for male target persons, using a 7-point Likert scale.

To test the causal effects of the manipulations, we used a between-subjects design in Studies 2a & 2b. Participants rated either warmth (for the images manipulated in facial expressions of emotion) or attractiveness (for the images manipulated in clothing styles) of each target person one by one in random order using a 7-point Likert scale. Each participant was randomly assigned to one manipulated version of the 147 target persons. The procedure was the same as in Study 1.

There were four attention checks throughout the experiment. For these checks, we randomly selected four images containing more than one person. After participants rated the selected image, two images appeared on the screen side by side: the original image they just rated and the same image with an arrow indicating a different person. Participants were asked to select the target person they just rated. After rating all images on a given trait, participants completed a questionnaire about their understanding of the trait and demographic information.

Analysis

For both manipulation checks and testing the causal effects, we conducted two pre-registered analysis: one at the aggregate-level using paired t-test, the other at the individual-level using linear mixed model. The paired t-test was based on aggregate ratings across participants. The linear mixed model was based on individual ratings and included both random slopes and random intercepts for participants and target persons.

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Supplementary Materials for

Cues driving trait impressions in naturalistic contexts are sparse

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Supplementary Tables

Table S1. Predictions of Each Coarse-category Cues on Each Trait Impression

Coarse-category Cues	Attractiveness			Competence			Dominance			Femininity		
	$\bar{r}$	p	SD	$\bar{r}$	p	SD	$\bar{r}$	p	SD	$\bar{r}$	p	SD
Face	0.07	0.05347326	±0.02	**0.10**	**0.0069965**	**±0.03**	**0.10**	**0.001999**	**±0.03**	**0.13**	**0.00049975**	**±0.01**
Body	0.04	0.24937531	±0.03	**0.13**	**0.0009995**	**±0.04**	**0.10**	**0.001999**	**±0.04**	0.00	0.50174913	±0.01
Clothing	**0.27**	**0.00049975**	**±0.04**	0.04	0.30734633	±0.02	**0.22**	**0.00049975**	**±0.04**	**0.90**	**0.00049975**	**±0.01**
Environment	0.02	0.45677161	±0.03	**0.11**	**0.00149925**	**±0.03**	**0.09**	**0.009995**	**±0.03**	0.02	0.09745127	±0.01

Coarse-category Cues	Openness			Warmth			Youthfulness		
	$\bar{r}$	p	SD	$\bar{r}$	p	SD	$\bar{r}$	p	SD
Face	**0.44**	**0.00049975**	**±0.04**	**0.79**	**0.00049975**	**±0.02**	**0.10**	**0.00149925**	**±0.02**
Body	**0.10**	**0.0069965**	**±0.03**	**0.20**	**0.00049975**	**±0.03**	0.01	0.48325837	±0.03
Clothing	-0.02	0.50724638	±0.02	0.03	0.25787106	±0.02	**0.27**	**0.00049975**	**±0.03**
Environment	**0.25**	**0.00049975**	**±0.05**	**0.20**	**0.00049975**	**±0.04**	0.01	0.48125937	±0.02

Note. Each model regressed distances in a trait impression on distances in all features from all cues belonging to a coarse category across image pairs (N = 632,250) using representational similarity analysis with Ridge regression and cross-validation to increase generalizability. Model accuracy, $\bar{r}$, indicates the mean prediction accuracy across 500 cross-validation iterations. Model prediction standard deviation, SD, were computed across the 500 cross-validation iterations. Model prediction significance, *p*s, were corrected for multiple testing across cues using maximal statistic permutation tests. Statistically significant predictions were highlighted in bold.

Table S2. Prediction of Each Fine-grained Cues on Each Trait Impression

Fine-grained Cues	Attractiveness			Competence			Dominance			Femininity		
	$\bar{r}$	p	SD	$\bar{r}$	p	SD	$\bar{r}$	p	SD	$\bar{r}$	p	SD
Expressions	0.01	0.50674663	±0.02	0.09	0.05897051	±0.03	0.06	0.32633683	±0.02	0.02	0.28735632	±0.01
Facial Structure	0.06	0.21889055	±0.02	0.03	0.50424788	±0.02	0.06	0.23938031	±0.02	**0.13**	**0.00049975**	**±0.01**
Gaze	-0.01	0.50674663	±0.02	0.05	0.38030985	±0.03	0.04	0.45077461	±0.03	0.00	0.51024488	±0.01
Skin Color	0.03	0.50324838	±0.03	0.03	0.50624688	±0.04	0.07	0.10394803	±0.05	0.01	0.50874563	±0.01
Shape	0.00	0.50674663	±0.03	0.03	0.50924538	±0.03	-0.01	0.50124938	±0.03	0.00	0.51024488	±0.01
Body Pose	0.03	0.50624688	±0.03	0.05	0.42828586	±0.03	0.02	0.50124938	±0.03	0.01	0.51024488	±0.01
Head Pose	0.02	0.50674663	±0.03	0.03	0.50974513	±0.03	-0.02	0.50124938	±0.02	0.00	0.51024488	±0.01
Action	0.03	0.49425287	±0.03	**0.13**	**0.0029985**	**±0.04**	**0.11**	**0.017991**	**±0.04**	0.00	0.51024488	±0.01
Clothing Color	0.03	0.50624688	±0.03	0.03	0.50274863	±0.03	0.03	0.49725137	±0.03	0.01	0.50974513	±0.01
Clothing Style	**0.24**	**0.00049975**	**±0.04**	0.03	0.50974513	±0.02	**0.21**	**0.00049975**	**±0.04**	**0.77**	**0.00049975**	**±0.02**
Hair Color	**0.10**	**0.0169915**	**±0.03**	0.01	0.50974513	±0.02	0.01	0.50124938	±0.02	**0.09**	**0.00049975**	**±0.03**
Hair Style	**0.25**	**0.00049975**	**±0.04**	0.02	0.50974513	±0.02	**0.19**	**0.00049975**	**±0.04**	**0.88**	**0.00049975**	**±0.01**
Complexity	0.00	0.50674663	±0.03	0.06	0.34182909	±0.03	0.02	0.50124938	±0.03	0.01	0.51024488	±0.01
Environment Color	0.03	0.50124938	±0.03	0.06	0.34882559	±0.03	0.03	0.49675162	±0.03	0.01	0.51024488	±0.01
Gist	0.01	0.50674663	±0.02	0.09	0.06146927	±0.02	0.09	0.05097451	±0.03	0.01	0.50224888	±0.01
Vibe	0.01	0.50674663	±0.03	0.06	0.24037981	±0.04	0.05	0.43728136	±0.04	0.02	0.22538731	±0.02

Fine-grained Cues	Openness			Warmth			Youthfulness		
	$\bar{r}$	p	SD	$\bar{r}$	p	SD	$\bar{r}$	p	SD
Expressions	**0.44**	**0.00049975**	**±0.04**	**0.79**	**0.00049975**	**±0.02**	0.00	0.50024988	±0.03
Facial Structure	0.03	0.49925037	±0.02	0.05	0.11894053	±0.01	**0.11**	**0.0069965**	**±0.02**
Gaze	0.05	0.37831084	±0.03	**0.09**	**0.00049975**	**±0.03**	-0.02	0.50024988	±0.02
Skin Color	0.02	0.50074963	±0.04	0.03	0.46576712	±0.03	-0.01	0.50024988	±0.03
Shape	0.03	0.49625187	±0.04	0.03	0.44577711	±0.02	-0.02	0.50074963	±0.02

Body Pose	0.06	0.22388806	±0.04	0.02	0.50974513	±0.02	-0.02	0.50024988	±0.02
Head Pose	0.06	0.33433283	±0.03	0.05	0.14642679	±0.02	0.02	0.49975012	±0.03
Action	0.09	0.05697151	±0.03	**0.19**	**0.00049975**	**±0.03**	0.02	0.49975012	±0.03
Clothing Color	0.00	0.50124938	±0.02	0.00	0.51024488	±0.02	-0.02	0.50024988	±0.02
Clothing Style	-0.02	0.50124938	±0.02	0.02	0.50224888	±0.02	0.07	0.13343328	±0.03
Hair Color	-0.01	0.50124938	±0.02	0.00	0.51024488	±0.02	**0.26**	**0.00049975**	**±0.03**
Hair Style	0.01	0.50124938	±0.02	0.03	0.4077961	±0.02	0.08	0.05847076	±0.03
Complexity	-0.01	0.50124938	±0.02	-0.01	0.51024488	±0.02	0.02	0.50024988	±0.02
Environment Color	0.01	0.50124938	±0.04	0.00	0.51024488	±0.02	0.02	0.50024988	±0.02
Gist	0.04	0.47676162	±0.02	0.01	0.51024488	±0.02	-0.01	0.50024988	±0.02
Vibe	**0.25**	**0.00049975**	**±0.05**	**0.20**	**0.00049975**	**±0.04**	0.00	0.50024988	±0.03

Note. Each model regressed distances in a trait impression on distances in all features belong to a cue across image pairs (N = 632,250) using representational similarity analysis with Ridge regression and cross-validation to increase generalizability. Model accuracy, $\bar{r}$, indicates the mean prediction accuracy across 500 cross-validation iterations. Model prediction standard deviation, SD, were computed across the 500 cross-validation iterations. Model prediction significance, *p*s, were corrected for multiple testing across cues using maximal statistic permutation tests. Statistically significant predictions were highlighted in bold.

Table S3. Unique and Common Explained Variance of Each Coarse-category Cue on Each Trait Impression

Coarse-category Cues	Attractiveness			Competence			Dominance			Femininity		
	$\Delta\lvert\bar{r}\rvert^2$	*p*	SD	$\Delta\lvert\bar{r}\rvert^2$	*p*	SD	$\Delta\lvert\bar{r}\rvert^2$	*p*	SD	$\Delta\lvert\bar{r}\rvert^2$	*p*	SD
Unique												
Face				0.002	0.22238881	±0.003	**0.004**	**0.02348826**	**±0.006**	**0.00038**	**0.04097951**	**±0.00039**
Body				**0.009**	**0.00049975**	**±0.006**	**0.006**	**0.00449775**	**±0.005**			
Clothing	**0.070**	**0.00049975**	**±0.020**				**0.042**	**0.00049975**	**±0.014**	**0.784**	**0.00049975**	**±0.018**
Environment				**0.008**	**0.00049975**	**±0.005**	**0.004**	**0.03698151**	**±0.004**	0.000	0.15692154	±0.001
Common												
Face				0.002	0.07146427	±0.007	0.001	0.10344828	±0.006	**0.017**	**0.00049975**	**±0.004**
Body				0.003	0.05147426	±0.007	0.000	0.13993003	±0.006			
Clothing	0.000	0.16141929	±0.006				-0.001	0.15042479	±0.006	**0.016**	**0.00049975**	**±0.004**
Environment				0.000	0.16241879	±0.007	-0.001	0.14042979	±0.006	0.000	0.57121439	±0.001

Coarse-category Cues	Openness			Warmth			Youthfulness		
	$\Delta\lvert\bar{r}\rvert^2$	*p*	SD	$\Delta\lvert\bar{r}\rvert^2$	*p*	SD	$\Delta\lvert\bar{r}\rvert^2$	*p*	SD
Unique									
Face	**0.149**	**0.00049975**	**±0.029**	**0.547**	**0.00049975**	**±0.026**	**0.007**	**0.00049975**	**±0.004**
Body	0.000	0.49575212	±0.004	**0.002**	**0.00949525**	**±0.002**			
Clothing							**0.066**	**0.00049975**	**±0.017**
Environment	**0.017**	**0.00049975**	**±0.011**	0.000	0.48075962	±0.001	0.000	0.49325337	±0.001
Common									
Face	**0.042**	**0.00049975**	**±0.017**	**0.071**	**0.00049975**	**±0.019**	-0.001	0.16491754	±0.006
Body	**0.004**	**0.01549225**	**±0.010**	**0.033**	**0.00049975**	**±0.012**			
Clothing							0.000	0.16041979	±0.006
Environment	**0.036**	**0.00049975**	**±0.016**	**0.038**	**0.00049975**	**±0.015**	-0.003	0.54972514	±0.005

Note. Each model regressed distances in a trait impression on distances in i) all features across all coarse-category cues, ii) only features about a specific coarse-category cue, or iii) all features except for those about a specific coarse-category cue, across image pairs (N = 632,250) using representational similarity analysis with Ridge regression and cross-validation to increase generalizability. As pre-reregistered, this variance partition analysis was only carried out for coarse-category cues that showed a significant prediction of a given trait impression; blanks in the table indicate that the coarse-category cue was not significant for predicting the given trait impression as indicated in Table S1. Mean absolute change in model explained variance, $\Delta|\bar{r}|^2$, indicates the average unique or common contribution of a given coarse-category cue compared to the rest of the coarse-category cues on a trait impression across the 500 cross-validation iterations, where the explained variance per model in each iteration was computed by squaring the prediction accuracy of the model (Pearson correlation between the predicted and observed ratings). Standard deviation in the change of these explained variances, SD, were computed across the 500 cross-validation iterations. The significance of the change in model explained variance, *p*s, were corrected for multiple testing across cues using maximal statistic permutation tests. Statistically significant predictions were highlighted in bold.

Table S4. Unique and Common Explained Variance of Each Fine-grained Cue on Each Trait Impression

Fine-grained Cues	Attractiveness			Competence			Dominance			Femininity		
	$\Delta\lvert\bar{r}\rvert^2$	*p*	SD	$\Delta\lvert\bar{r}\rvert^2$	*p*	SD	$\Delta\lvert\bar{r}\rvert^2$	*p*	SD	$\Delta\lvert\bar{r}\rvert^2$	*p*	SD
Unique												
Expressions												
Facial Structure										**0.001**	**0.015992**	**±0.041**
Gaze												
Skin Color												
Shape												
Body Pose												
Head Pose												
Action				**0.008**	**0.0009995**	**±0.038**	**0.006**	**0.003998**	**±0.041**			
Clothing Color												
Clothing Style	**0.005**	**0.01149425**	**±0.042**				**0.011**	**0.00049975**	**±0.041**	**0.030**	**0.00049975**	**±0.042**
Hair Color	**0.005**	**0.007996**	**±0.042**							0.000	0.55222389	±0.041
Hair Style	**0.011**	**0.00049975**	**±0.042**				0.001	0.35382309	±0.042	**0.212**	**0.00049975**	**±0.049**
Complexity												
Environment Color												
Gist												
Vibe												
Common												
Expressions												
Facial Structure										**0.017**	**0.00049975**	**±0.041**
Gaze												
Skin Color												
Shape												
Body Pose												
Head Pose												

Action				**0.004**	**0.00349825**	**±0.041**	0.001	0.14442779	±0.043			
Clothing Color												
Clothing Style	**0.047**	**0.00049975**	**±0.054**				**0.028**	**0.00049975**	**±0.048**	**0.554**	**0.00049975**	**±0.056**
Hair Color	0.000	0.1814093	±0.045							**0.008**	**0.00049975**	**±0.041**
Hair Style	**0.048**	**0.00049975**	**±0.053**				**0.028**	**0.00049975**	**±0.048**	**0.560**	**0.00049975**	**±0.056**
Complexity												
Environment Color												
Gist												
Vibe												

Fine-grained Cues	Openness			Warmth			Youthfulness		
	$\Delta\lvert\bar{r}\rvert^2$	p	SD	$\Delta\lvert\bar{r}\rvert^2$	p	SD	$\Delta\lvert\bar{r}\rvert^2$	p	SD
Unique									
Expressions	**0.150**	**0.00049975**	**±0.029**	**0.546**	**0.00049975**	**±0.037**			
Facial Structure							**0.007**	**0.00049975**	**±0.042**
Gaze				0.000	0.48025987	±0.041			
Skin Color									
Shape									
Body Pose									
Head Pose									
Action				0.001	0.14392804	±0.041			
Clothing Color									
Clothing Style									
Hair Color							**0.062**	**0.00049975**	**±0.038**
Hair Style									
Complexity									
Environment Color									
Gist									

Vibe	**0.016**	**0.00049975**	**±0.010**	0.000	0.49625187	±0.041			
Common									
Expressions	**0.042**	**0.00049975**	**±0.017**	**0.072**	**0.00049975**	**±0.047**			
Facial Structure							0.000	0.16141929	±0.043
Gaze				**0.005**	**0.00049975**	**±0.042**			
Skin Color									
Shape									
Body Pose									
Head Pose									
Action				**0.033**	**0.00049975**	**±0.045**			
Clothing Color									
Clothing Style									
Hair Color							**0.002**	**0.04847576**	**±0.043**
Hair Style									
Complexity									
Environment Color									
Gist									
Vibe	**0.037**	**0.00049975**	**±0.016**	**0.038**	**0.00049975**	**±0.044**			

Note. Each model regressed distances in a trait impression on distances in i) all features across all fine-grained cues, ii) only features about a specific fine-grained cue, or iii) all features except for those about a specific fine-grained cue, across image pairs (N = 632,250) using representational similarity analysis with Ridge regression and cross-validation to increase generalizability. As pre-reregistered, this variance partition analysis was only carried out for fine-grained cues that showed a significant prediction of a given trait impression; blanks in the table indicate that the fine-grained cue was not significant for predicting the given trait impression as indicated in Table S2. Mean absolute change in model explained variance, $\Delta|\bar{r}|^2$, indicates the average unique or common contribution of a given fine-grained cue compared to the rest of the fine-grained cues on a trait impression across the 500 cross-validation iterations, where the explained variance per model in each iteration was computed by squaring the prediction accuracy of the model (Pearson correlation between the predicted and observed ratings). Standard deviation in the change of these explained variances, SD, were computed across the 500 cross-validation iterations. The significance of the change in model explained variance, *p*s, were corrected for multiple testing across cues using maximal statistic permutation tests. Statistically significant predictions were highlighted in bold.

Table S5. Two-way Interactions between All Coarse-Category Cues on Each Trait Impression

Coarse-category Cues and Two-way Interaction	Attractiveness			Competence			Dominance			Femininity		
	β	95% CI	sig	β	95% CI	sig	β	95% CI	sig	β	95% CI	sig
Face	-0.009	[-0.054, 0.030]		0.055	[0.062, 0.160]	*	0.084	[0.084, 0.189]	*	0.001	[-0.030, 0.020]	
Body	-0.003	[-0.047, 0.043]		0.060	[0.064, 0.175]	*	0.031	[0.000, 0.102]		0.064	[0.010, 0.055]	*
Clothing	0.299	[0.352, 0.466]	*	0.019	[0.007, 0.068]	*	0.173	[0.225, 0.329]	*	2.331	[1.160, 1.201]	*
Environment	0.019	[-0.022, 0.073]		0.089	[0.129, 0.234]	*	0.075	[0.070, 0.171]	*	0.010	[-0.021, 0.026]	
Face × Body	0.013	[-0.026, 0.043]		-0.007	[-0.051, 0.039]		-0.009	[-0.049, 0.036]		-0.029	[-0.018, 0.029]	
Face × Clothing	-0.034	[-0.105, -0.008]	*	-0.007	[-0.037, 0.023]		0.014	[-0.016, 0.080]		0.025	[0.004, 0.057]	*
Face × Environment	0.009	[-0.036, 0.035]		-0.004	[-0.046, 0.057]		-0.016	[-0.059, 0.025]		-0.025	[-0.003, 0.040]	
Body × Clothing	-0.005	[-0.059, 0.042]		-0.004	[-0.036, 0.024]		-0.045	[-0.124, -0.014]	*	0.018	[-0.016, 0.047]	
Body × Environment	-0.019	[-0.071, 0.008]		-0.001	[-0.042, 0.053]		0.016	[-0.015, 0.082]		-0.018	[-0.020, 0.025]	
Clothing × Environment	0.030	[-0.021, 0.094]		-0.029	[-0.085, -0.029]	*	-0.002	[-0.046, 0.048]		0.014	[-0.010, 0.050]	

Coarse-category Cues and Two-way Interaction	Openness			Warmth			Youthfulness		
	β	95% CI	sig	β	95% CI	sig	β	95% CI	sig
Face	0.239	[0.367, 0.481]	*	0.686	[0.757, 0.828]	*	0.053	[0.021, 0.110]	*
Body	0.040	[0.011, 0.120]	*	0.019	[-0.019, 0.056]		0.000	[-0.045, 0.046]	
Clothing	-0.018	[-0.062, 0.000]	*	-0.026	[-0.057, -0.002]	*	0.218	[0.222, 0.308]	*
Environment	0.115	[0.145, 0.259]	*	0.077	[0.048, 0.120]	*	-0.039	[-0.082, -0.006]	*
Face × Body	0.047	[0.026, 0.135]	*	0.041	[0.022, 0.119]	*	-0.004	[-0.053, 0.021]	
Face × Clothing	-0.030	[-0.101, -0.020]	*	-0.012	[-0.036, 0.035]		-0.057	[-0.120, -0.041]	*
Face × Environment	0.032	[-0.005, 0.104]		0.025	[0.007, 0.109]	*	0.006	[-0.037, 0.025]	
Body × Clothing	-0.005	[-0.042, 0.020]		-0.017	[-0.041, 0.014]		0.037	[0.003, 0.085]	*
Body × Environment	0.031	[-0.011, 0.111]		-0.024	[-0.055, 0.025]		0.019	[-0.018, 0.055]	
Clothing × Environment	-0.006	[-0.050, 0.018]		0.022	[0.008, 0.066]	*	-0.010	[-0.056, 0.023]	

Note. Each model regressed the distances in each trait impression on the distances in each coarse-category cue and all pairwise two-way interactions between them across image pairs (N = 632,250) using representational similarity analysis with Ridge regression and cross-validation to increase generalizability. Effect size β indicates the standardized coefficient in the model (both the dependent variables and the independent variables in all pre-registered analyses were standardized). The significance of these effect sizes was estimated using bootstrap resampling as pre-registered where each bootstrap iteration selects a new set of images with replacement and computes their distances. The 95% confidence interval indicates the effect sizes fall within the 2.5% and 97.5% of the effect sizes across the 2000 bootstrap iterations. The significance, sig, indicates whether the lower-bound of this 95% confidence interval overlaps with zero. Statistically significant effects were indicated with asterisks.

Table S6. Two-way Interactions between All Fine-grained Cues on Each Trait Impression

Fine-grained Cues and Two-way Interaction	Attractiveness			Competence			Dominance			Femininity		
	β	95% CI	sig	β	95% CI	sig	β	95% CI	sig	β	95% CI	sig
Expressions	0.001	[-0.017, 0.021]		0.022	[0.023, 0.067]	*	0.015	[0.006, 0.045]	*	-0.009	[-0.014, 0.006]	
Facial Structure	0.021	[0.016, 0.047]	*	0.008	[0.003, 0.030]	*	0.014	[0.009, 0.040]	*	0.049	[0.016, 0.033]	*
Gaze	-0.005	[-0.027, 0.014]		0.008	[-0.005, 0.038]		0.012	[-0.002, 0.044]		0.000	[-0.009, 0.009]	
Skin Color	-0.024	[-0.056, -0.011]	*	0.007	[-0.008, 0.038]		0.032	[0.020, 0.087]	*	-0.005	[-0.014, 0.009]	
Shape	0.003	[-0.017, 0.030]		0.005	[-0.013, 0.035]		-0.004	[-0.030, 0.020]		0.021	[0.001, 0.021]	*
Body Pose	-0.013	[-0.040, 0.002]		0.011	[-0.001, 0.046]		0.008	[-0.010, 0.038]		0.021	[0.002, 0.020]	*
Head Pose	-0.011	[-0.036, 0.006]		0.001	[-0.018, 0.025]		-0.008	[-0.037, 0.012]		0.021	[-0.001, 0.020]	
Action	0.023	[0.009, 0.057]	*	0.037	[0.050, 0.104]	*	0.044	[0.045, 0.105]	*	-0.007	[-0.014, 0.007]	
Clothing Color	0.013	[-0.003, 0.041]		0.011	[0.006, 0.043]	*	0.012	[0.000, 0.040]		0.006	[-0.006, 0.011]	
Clothing Style	0.072	[0.058, 0.133]	*	0.007	[-0.004, 0.036]		0.074	[0.094, 0.157]	*	0.515	[0.223, 0.294]	*
Hair Color	0.048	[0.046, 0.092]	*	-0.006	[-0.027, 0.002]		-0.005	[-0.029, 0.011]		0.003	[-0.009, 0.012]	
Hair Style	0.103	[0.114, 0.182]	*	0.004	[-0.008, 0.024]		0.046	[0.043, 0.106]	*	1.343	[0.647, 0.715]	*
Complexity	0.004	[-0.015, 0.028]		0.014	[0.009, 0.050]	*	0.004	[-0.013, 0.025]		-0.002	[-0.010, 0.008]	
Environment Color	0.015	[-0.002, 0.045]		0.014	[0.009, 0.051]	*	0.008	[-0.008, 0.036]		-0.017	[-0.020, 0.003]	
Gist	0.000	[-0.018, 0.016]		0.025	[0.034, 0.071]	*	0.033	[0.036, 0.078]	*	-0.037	[-0.029, -0.009]	*
Vibe	-0.007	[-0.032, 0.012]		0.017	[0.009, 0.063]	*	0.017	[-0.005, 0.063]		0.024	[0.002, 0.022]	*
Expressions × Facial Structure	-0.004	[-0.013, 0.002]		0.001	[-0.006, 0.011]		-0.004	[-0.014, 0.003]		-0.012	[-0.010, -0.001]	*
Expressions × Gaze	-0.001	[-0.014, 0.013]		-0.007	[-0.030, 0.001]		-0.006	[-0.027, 0.006]		0.002	[-0.006, 0.008]	
Expressions × Skin Color	0.002	[-0.008, 0.013]		0.000	[-0.013, 0.013]		0.003	[-0.009, 0.020]		0.002	[-0.005, 0.007]	
Expressions × Shape	0.004	[-0.003, 0.016]		-0.004	[-0.023, 0.004]		0.003	[-0.004, 0.017]		0.002	[-0.004, 0.006]	
Expressions × Body Pose	0.004	[-0.005, 0.015]		0.004	[-0.006, 0.021]		-0.001	[-0.014, 0.009]		0.001	[-0.005, 0.006]	
Expressions × Head Pose	0.005	[-0.003, 0.018]		0.002	[-0.008, 0.018]		0.001	[-0.010, 0.012]		-0.001	[-0.006, 0.005]	
Expressions × Action	-0.004	[-0.019, 0.008]		-0.015	[-0.046, -0.018]	*	-0.005	[-0.023, 0.007]		-0.004	[-0.009, 0.005]	
Expressions × Clothing Color	-0.002	[-0.013, 0.005]		0.002	[-0.005, 0.014]		0.002	[-0.006, 0.014]		0.008	[0.000, 0.009]	*

Expressions × Clothing Style	-0.003	[-0.021, 0.011]		-0.004	[-0.022, 0.003]		0.006	[-0.005, 0.026]		-0.014	[-0.022, 0.008]	
Expressions × Hair Color	0.001	[-0.009, 0.013]		-0.002	[-0.012, 0.005]		0.001	[-0.007, 0.011]		0.001	[-0.004, 0.005]	
Expressions × Hair Style	0.002	[-0.014, 0.018]		0.006	[0.003, 0.026]	*	0.003	[-0.011, 0.020]		0.010	[-0.009, 0.019]	
Expressions × Complexity	0.000	[-0.011, 0.010]		0.001	[-0.008, 0.014]		0.004	[-0.003, 0.018]		0.009	[-0.001, 0.010]	
Expressions × Environment Color	0.001	[-0.010, 0.012]		-0.008	[-0.028, -0.004]	*	-0.002	[-0.014, 0.010]		-0.002	[-0.010, 0.006]	
Expressions × Gist	0.002	[-0.004, 0.011]		0.006	[0.004, 0.024]	*	0.000	[-0.010, 0.010]		0.012	[0.002, 0.012]	*
Expressions × Vibe	0.002	[-0.010, 0.015]		-0.001	[-0.022, 0.015]		-0.013	[-0.041, -0.005]	*	-0.003	[-0.008, 0.004]	
Facial Structure × Gaze	0.000	[-0.009, 0.008]		-0.003	[-0.013, 0.002]		0.002	[-0.005, 0.013]		-0.003	[-0.006, 0.003]	
Facial Structure × Skin Color	-0.013	[-0.029, -0.009]	*	0.001	[-0.007, 0.011]		0.003	[-0.010, 0.018]		-0.018	[-0.015, -0.003]	*
Facial Structure × Shape	0.003	[-0.005, 0.012]		-0.002	[-0.012, 0.005]		-0.002	[-0.011, 0.005]		0.001	[-0.002, 0.007]	
Facial Structure × Body Pose	-0.006	[-0.018, 0.000]		-0.002	[-0.012, 0.003]		0.001	[-0.005, 0.011]		-0.003	[-0.005, 0.004]	
Facial Structure × Head Pose	-0.001	[-0.010, 0.006]		-0.001	[-0.011, 0.006]		0.001	[-0.007, 0.011]		0.003	[-0.002, 0.008]	
Facial Structure × Action	0.005	[-0.001, 0.017]		0.001	[-0.007, 0.010]		-0.007	[-0.022, 0.001]		0.003	[-0.001, 0.008]	
Facial Structure × Clothing Color	0.004	[-0.001, 0.014]		-0.002	[-0.010, 0.003]		-0.003	[-0.012, 0.003]		-0.003	[-0.004, 0.003]	
Facial Structure × Clothing Style	0.001	[-0.013, 0.015]		-0.002	[-0.012, 0.003]		-0.003	[-0.017, 0.007]		0.001	[-0.012, 0.014]	
Facial Structure × Hair Color	0.002	[-0.007, 0.012]		-0.001	[-0.010, 0.005]		0.000	[-0.008, 0.008]		-0.006	[-0.005, 0.004]	
Facial Structure × Hair Style	-0.005	[-0.021, 0.007]		-0.002	[-0.013, 0.003]		-0.003	[-0.016, 0.009]		0.007	[-0.007, 0.016]	
Facial Structure × Complexity	-0.002	[-0.010, 0.005]		0.001	[-0.004, 0.010]		0.001	[-0.006, 0.009]		0.005	[-0.001, 0.007]	
Facial Structure × Environment Color	0.002	[-0.007, 0.014]		0.000	[-0.007, 0.009]		-0.001	[-0.009, 0.008]		0.003	[-0.002, 0.007]	
Facial Structure × Gist	-0.001	[-0.009, 0.005]		0.002	[-0.002, 0.009]		0.004	[0.003, 0.016]	*	-0.001	[0.002, 0.009]	*
Facial Structure × Vibe	-0.002	[-0.012, 0.005]		0.000	[-0.011, 0.009]		-0.011	[-0.029, -0.008]	*	0.002	[-0.003, 0.006]	
Gaze × Skin Color	0.004	[-0.005, 0.016]		-0.002	[-0.016, 0.009]		-0.015	[-0.047, -0.005]	*	0.007	[-0.002, 0.009]	
Gaze × Shape	0.003	[-0.007, 0.016]		0.000	[-0.012, 0.012]		0.000	[-0.012, 0.014]		0.006	[-0.001, 0.008]	
Gaze × Body Pose	0.006	[-0.002, 0.021]		0.002	[-0.011, 0.017]		0.000	[-0.015, 0.014]		0.001	[-0.005, 0.006]	
Gaze × Head Pose	-0.013	[-0.034, -0.004]	*	-0.001	[-0.017, 0.013]		-0.004	[-0.021, 0.010]		0.001	[-0.007, 0.007]	

Gaze × Action	0.005	[-0.010, 0.021]		0.005	[-0.006, 0.028]		0.001	[-0.018, 0.020]		-0.013	[-0.014, 0.000]	*
Gaze × Clothing Color	-0.003	[-0.015, 0.007]		0.005	[0.001, 0.021]	*	0.002	[-0.009, 0.014]		0.001	[-0.004, 0.005]	
Gaze × Clothing Style	0.000	[-0.020, 0.020]		0.003	[-0.002, 0.018]		0.004	[-0.009, 0.025]		0.017	[-0.009, 0.026]	
Gaze × Hair Color	0.003	[-0.006, 0.016]		-0.002	[-0.013, 0.003]		-0.003	[-0.017, 0.006]		-0.004	[-0.007, 0.003]	
Gaze × Hair Style	-0.011	[-0.035, 0.002]		-0.004	[-0.018, -0.001]	*	-0.003	[-0.021, 0.009]		-0.007	[-0.019, 0.011]	
Gaze × Complexity	0.008	[0.001, 0.021]	*	0.001	[-0.008, 0.012]		0.003	[-0.006, 0.016]		0.003	[-0.003, 0.007]	
Gaze × Environment Color	0.004	[-0.007, 0.017]		0.008	[0.006, 0.028]	*	0.010	[0.005, 0.031]	*	-0.001	[-0.007, 0.006]	
Gaze × Gist	0.005	[-0.001, 0.015]		0.003	[-0.004, 0.016]		0.004	[-0.004, 0.021]		0.004	[-0.003, 0.006]	
Gaze × Vibe	-0.004	[-0.018, 0.005]		-0.007	[-0.030, 0.001]		-0.009	[-0.034, 0.003]		-0.017	[-0.014, -0.002]	*
Skin Color × Shape	0.003	[-0.007, 0.013]		0.001	[-0.010, 0.014]		0.000	[-0.016, 0.016]		-0.005	[-0.008, 0.002]	
Skin Color × Body Pose	0.000	[-0.011, 0.010]		0.003	[-0.008, 0.019]		0.008	[-0.004, 0.035]		0.008	[-0.002, 0.009]	
Skin Color × Head Pose	-0.003	[-0.014, 0.006]		-0.006	[-0.026, 0.002]		-0.004	[-0.024, 0.010]		0.002	[-0.005, 0.007]	
Skin Color × Action	0.001	[-0.014, 0.018]		0.009	[-0.003, 0.042]		0.000	[-0.028, 0.027]		-0.004	[-0.009, 0.005]	
Skin Color × Clothing Color	-0.006	[-0.021, 0.005]		0.001	[-0.011, 0.015]		0.000	[-0.015, 0.015]		0.003	[-0.005, 0.007]	
Skin Color × Clothing Style	-0.002	[-0.025, 0.020]		0.001	[-0.010, 0.017]		0.001	[-0.024, 0.025]		0.024	[-0.006, 0.031]	
Skin Color × Hair Color	-0.012	[-0.030, -0.004]	*	-0.001	[-0.013, 0.008]		-0.003	[-0.020, 0.008]		0.007	[-0.004, 0.010]	
Skin Color × Hair Style	-0.007	[-0.027, 0.008]		-0.002	[-0.017, 0.006]		0.004	[-0.014, 0.029]		-0.018	[-0.025, 0.005]	
Skin Color × Complexity	-0.003	[-0.014, 0.006]		-0.001	[-0.015, 0.013]		0.000	[-0.018, 0.018]		-0.007	[-0.009, 0.002]	
Skin Color × Environment Color	-0.001	[-0.014, 0.010]		0.000	[-0.015, 0.017]		0.004	[-0.015, 0.031]		-0.009	[-0.014, 0.005]	
Skin Color × Gist	-0.002	[-0.013, 0.008]		0.003	[-0.005, 0.019]		0.006	[-0.007, 0.027]		0.001	[-0.006, 0.005]	
Skin Color × Vibe	0.005	[-0.004, 0.018]		-0.009	[-0.034, -0.002]	*	-0.010	[-0.043, 0.007]		-0.006	[-0.009, 0.003]	
Shape × Body Pose	0.004	[-0.010, 0.021]		0.002	[-0.015, 0.026]		-0.004	[-0.022, 0.010]		-0.012	[-0.012, 0.000]	*
Shape × Head Pose	-0.005	[-0.020, 0.006]		0.002	[-0.007, 0.017]		-0.001	[-0.014, 0.011]		-0.004	[-0.008, 0.004]	
Shape × Action	-0.004	[-0.019, 0.007]		0.002	[-0.011, 0.020]		0.009	[-0.002, 0.030]		0.009	[-0.001, 0.010]	
Shape × Clothing Color	0.002	[-0.009, 0.014]		0.002	[-0.005, 0.015]		0.008	[0.001, 0.029]	*	0.001	[-0.005, 0.005]	
Shape × Clothing Style	0.014	[0.003, 0.039]	*	-0.001	[-0.012, 0.009]		-0.008	[-0.031, 0.007]		0.009	[-0.012, 0.024]	
Shape × Hair Color	-0.007	[-0.022, 0.003]		0.000	[-0.009, 0.008]		-0.003	[-0.015, 0.006]		-0.009	[-0.009, 0.001]	

Shape × Hair Style	0.007	[-0.006, 0.026]		-0.003	[-0.015, 0.002]		-0.011	[-0.038, -0.002]	*	-0.001	[-0.016, 0.012]	
Shape × Complexity	-0.005	[-0.020, 0.004]		-0.001	[-0.016, 0.010]		-0.001	[-0.013, 0.010]		-0.003	[-0.008, 0.005]	
Shape × Environment Color	-0.003	[-0.017, 0.008]		0.000	[-0.014, 0.015]		0.002	[-0.008, 0.016]		-0.006	[-0.009, 0.004]	
Shape × Gist	-0.002	[-0.013, 0.006]		-0.003	[-0.016, 0.004]		-0.003	[-0.018, 0.007]		-0.015	[-0.012, -0.001]	*
Shape × Vibe	-0.001	[-0.012, 0.010]		-0.003	[-0.021, 0.007]		-0.007	[-0.028, 0.003]		0.001	[-0.005, 0.005]	
Body Pose × Head Pose	0.001	[-0.011, 0.014]		0.002	[-0.013, 0.021]		-0.003	[-0.023, 0.010]		0.000	[-0.007, 0.006]	
Body Pose × Action	-0.006	[-0.021, 0.005]		0.007	[0.001, 0.032]	*	0.013	[0.005, 0.041]	*	-0.017	[-0.015, -0.003]	*
Body Pose × Clothing Color	0.002	[-0.008, 0.013]		0.003	[-0.005, 0.017]		-0.005	[-0.019, 0.001]		0.000	[-0.004, 0.005]	
Body Pose × Clothing Style	-0.015	[-0.042, -0.005]	*	0.001	[-0.007, 0.012]		0.006	[-0.006, 0.029]		0.019	[-0.008, 0.026]	
Body Pose × Hair Color	-0.002	[-0.014, 0.011]		0.004	[0.000, 0.017]		0.000	[-0.010, 0.011]		-0.009	[-0.010, 0.000]	
Body Pose × Hair Style	0.000	[-0.019, 0.021]		0.000	[-0.009, 0.009]		0.000	[-0.018, 0.019]		-0.024	[-0.028, 0.004]	
Body Pose × Complexity	0.000	[-0.011, 0.011]		0.002	[-0.008, 0.016]		0.004	[-0.005, 0.019]		0.003	[-0.004, 0.007]	
Body Pose × Environment Color	-0.008	[-0.023, 0.000]	*	0.003	[-0.005, 0.018]		-0.001	[-0.012, 0.010]		0.001	[-0.005, 0.006]	
Body Pose × Gist	0.007	[0.002, 0.019]	*	0.001	[-0.010, 0.012]		0.003	[-0.008, 0.018]		0.009	[0.000, 0.010]	
Body Pose × Vibe	-0.005	[-0.018, 0.004]		0.002	[-0.011, 0.021]		0.003	[-0.014, 0.024]		-0.001	[-0.005, 0.004]	
Head Pose × Action	-0.008	[-0.024, 0.002]		0.003	[-0.006, 0.022]		0.006	[-0.007, 0.031]		0.001	[-0.005, 0.007]	
Head Pose × Clothing Color	0.006	[-0.003, 0.021]		-0.003	[-0.015, 0.004]		-0.008	[-0.024, -0.003]	*	0.003	[-0.003, 0.006]	
Head Pose × Clothing Style	-0.004	[-0.026, 0.013]		0.002	[-0.007, 0.013]		0.006	[-0.006, 0.028]		0.023	[-0.006, 0.030]	
Head Pose × Hair Color	-0.007	[-0.022, 0.001]		0.002	[-0.003, 0.012]		0.000	[-0.012, 0.010]		0.011	[0.000, 0.011]	*
Head Pose × Hair Style	0.001	[-0.015, 0.021]		0.001	[-0.009, 0.012]		-0.006	[-0.031, 0.009]		-0.015	[-0.024, 0.008]	
Head Pose × Complexity	0.000	[-0.011, 0.009]		-0.002	[-0.018, 0.010]		0.001	[-0.011, 0.014]		-0.004	[-0.008, 0.003]	
Head Pose × Environment Color	-0.001	[-0.012, 0.009]		-0.003	[-0.016, 0.005]		0.002	[-0.008, 0.012]		0.009	[-0.002, 0.011]	
Head Pose × Gist	-0.002	[-0.011, 0.006]		-0.001	[-0.012, 0.008]		-0.007	[-0.025, 0.000]	*	0.006	[-0.002, 0.009]	
Head Pose × Vibe	0.000	[-0.010, 0.012]		-0.003	[-0.019, 0.006]		0.009	[-0.003, 0.039]		0.004	[-0.003, 0.007]	
Action × Clothing Color	-0.007	[-0.021, 0.002]		-0.003	[-0.020, 0.006]		0.003	[-0.008, 0.019]		-0.005	[-0.006, 0.003]	
Action × Clothing Style	0.006	[-0.014, 0.032]		-0.004	[-0.021, 0.006]		-0.009	[-0.036, 0.008]		-0.011	[-0.023, 0.014]	

Action × Hair Color	0.003	[-0.008, 0.017]		-0.003	[-0.016, 0.004]		0.002	[-0.009, 0.015]		0.007	[-0.002, 0.009]	
Action × Hair Style	-0.002	[-0.024, 0.016]		-0.003	[-0.017, 0.005]		-0.012	[-0.040, 0.000]		0.006	[-0.015, 0.019]	
Action × Complexity	-0.002	[-0.015, 0.008]		0.004	[-0.005, 0.022]		0.004	[-0.008, 0.021]		0.007	[-0.002, 0.009]	
Action × Environment Color	0.004	[-0.011, 0.022]		0.008	[0.003, 0.030]	*	0.001	[-0.015, 0.018]		0.002	[-0.006, 0.008]	
Action × Gist	-0.001	[-0.011, 0.008]		0.002	[-0.008, 0.016]		0.003	[-0.008, 0.020]		-0.008	[-0.008, 0.002]	
Action × Vibe	0.000	[-0.013, 0.015]		-0.009	[-0.035, -0.002]	*	0.003	[-0.016, 0.029]		0.001	[-0.005, 0.006]	
Clothing Color × Clothing Style	0.002	[-0.019, 0.024]		0.003	[-0.003, 0.017]		0.005	[-0.008, 0.025]		-0.040	[-0.033, -0.007]	*
Clothing Color × Hair Color	-0.004	[-0.017, 0.004]		-0.002	[-0.013, 0.005]		-0.001	[-0.012, 0.009]		0.002	[-0.004, 0.006]	
Clothing Color × Hair Style	-0.003	[-0.020, 0.009]		-0.001	[-0.009, 0.004]		-0.004	[-0.023, 0.006]		0.030	[0.003, 0.027]	*
Clothing Color × Complexity	0.009	[0.001, 0.025]	*	0.003	[-0.004, 0.017]		0.004	[-0.003, 0.017]		0.009	[-0.001, 0.010]	
Clothing Color × Environment Color	-0.001	[-0.013, 0.010]		0.001	[-0.008, 0.010]		0.006	[0.000, 0.022]	*	0.014	[0.002, 0.013]	*
Clothing Color × Gist	-0.001	[-0.011, 0.007]		0.001	[-0.006, 0.011]		0.001	[-0.006, 0.011]		0.003	[-0.002, 0.007]	
Clothing Color × Vibe	0.002	[-0.008, 0.014]		-0.006	[-0.024, 0.000]	*	-0.011	[-0.032, -0.006]	*	0.005	[-0.002, 0.008]	
Clothing Style × Hair Color	0.002	[-0.018, 0.020]		0.002	[-0.005, 0.014]		-0.002	[-0.020, 0.009]		0.013	[-0.011, 0.023]	
Clothing Style × Hair Style	0.044	[0.046, 0.082]	*	-0.004	[-0.022, 0.004]		0.013	[0.004, 0.039]	*	0.055	[0.019, 0.038]	*
Clothing Style × Complexity	-0.004	[-0.023, 0.013]		0.001	[-0.008, 0.013]		-0.012	[-0.036, -0.006]	*	0.002	[-0.014, 0.016]	
Clothing Style × Environment Color	0.002	[-0.020, 0.028]		-0.007	[-0.028, -0.004]	*	-0.008	[-0.034, 0.004]		-0.018	[-0.026, 0.010]	
Clothing Style × Gist	0.001	[-0.015, 0.018]		-0.004	[-0.018, 0.003]		0.000	[-0.016, 0.017]		-0.042	[-0.038, -0.003]	*
Clothing Style × Vibe	0.016	[0.004, 0.042]	*	-0.006	[-0.025, 0.000]	*	0.012	[0.003, 0.038]	*	0.010	[-0.011, 0.021]	
Hair Color × Hair Style	0.006	[-0.009, 0.028]		0.001	[-0.009, 0.011]		0.009	[0.002, 0.032]	*	-0.010	[-0.020, 0.010]	
Hair Color × Complexity	-0.003	[-0.014, 0.006]		-0.004	[-0.016, -0.001]	*	-0.005	[-0.017, 0.001]		-0.004	[-0.006, 0.003]	
Hair Color × Environment Color	0.009	[0.001, 0.026]	*	-0.002	[-0.012, 0.005]		0.003	[-0.005, 0.016]		0.000	[-0.006, 0.005]	
Hair Color × Gist	-0.003	[-0.013, 0.005]		-0.002	[-0.011, 0.004]		-0.005	[-0.019, 0.003]		-0.001	[-0.005, 0.005]	
Hair Color × Vibe	-0.006	[-0.021, 0.004]		-0.001	[-0.009, 0.007]		0.004	[-0.006, 0.020]		0.011	[0.000, 0.010]	*
Hair Style × Complexity	-0.002	[-0.020, 0.014]		-0.001	[-0.011, 0.004]		-0.002	[-0.016, 0.014]		0.002	[-0.013, 0.014]	

Hair Style × Environment Color	-0.005	[-0.030, 0.011]		0.001	[-0.004, 0.012]		0.004	[-0.006, 0.024]		0.017	[-0.008, 0.024]	
Hair Style × Gist	-0.003	[-0.019, 0.011]		-0.002	[-0.011, 0.004]		0.003	[-0.008, 0.020]		0.032	[0.001, 0.030]	*
Hair Style × Vibe	0.012	[-0.001, 0.035]		0.000	[-0.010, 0.011]		0.002	[-0.016, 0.020]		-0.006	[-0.018, 0.011]	
Complexity × Environment Color	-0.005	[-0.019, 0.006]		0.002	[-0.008, 0.016]		-0.001	[-0.013, 0.009]		0.003	[-0.005, 0.008]	
Complexity × Gist	0.000	[-0.010, 0.012]		0.002	[-0.007, 0.016]		-0.001	[-0.014, 0.010]		0.001	[-0.005, 0.008]	
Complexity × Vibe	0.002	[-0.008, 0.013]		-0.001	[-0.014, 0.011]		-0.004	[-0.025, 0.009]		0.001	[-0.005, 0.005]	
Environment Color × Gist	0.001	[-0.010, 0.013]		0.002	[-0.006, 0.015]		0.002	[-0.009, 0.018]		-0.012	[-0.013, 0.001]	
Environment Color × Vibe	-0.001	[-0.014, 0.013]		0.001	[-0.013, 0.016]		-0.003	[-0.021, 0.009]		-0.004	[-0.007, 0.004]	
Gist × Vibe	-0.010	[-0.024, -0.004]	*	-0.003	[-0.017, 0.006]		0.000	[-0.013, 0.016]		-0.010	[-0.010, 0.000]	

Coarse-category Cues and Two-way Interaction	Openness			Warmth			Youthfulness		
	β	95% CI	sig	β	95% CI	sig	β	95% CI	sig
Expressions	0.216	[0.338, 0.415]	*	0.687	[0.758, 0.800]	*	0.006	[-0.013, 0.028]	
Facial Structure	-0.002	[-0.020, 0.013]		0.002	[-0.009, 0.013]		0.064	[0.065, 0.099]	*
Gaze	-0.002	[-0.029, 0.022]		-0.017	[-0.037, -0.003]	*	0.000	[-0.019, 0.021]	
Skin Color	0.003	[-0.021, 0.034]		-0.003	[-0.024, 0.018]		-0.027	[-0.056, -0.008]	*
Shape	0.009	[-0.015, 0.046]		0.028	[0.014, 0.048]	*	0.010	[-0.013, 0.039]	
Body Pose	0.019	[0.005, 0.065]	*	-0.031	[-0.052, -0.017]	*	-0.004	[-0.026, 0.019]	
Head Pose	0.010	[-0.010, 0.044]		-0.011	[-0.031, 0.006]		-0.018	[-0.046, -0.001]	*
Action	-0.002	[-0.036, 0.026]		0.035	[0.018, 0.060]	*	0.016	[-0.004, 0.043]	
Clothing Color	-0.007	[-0.028, 0.005]		-0.004	[-0.017, 0.008]		-0.003	[-0.022, 0.016]	
Clothing Style	-0.003	[-0.034, 0.024]		-0.005	[-0.024, 0.013]		0.010	[-0.017, 0.039]	
Hair Color	0.008	[-0.007, 0.035]		0.000	[-0.010, 0.011]		0.200	[0.212, 0.279]	*
Hair Style	0.001	[-0.021, 0.028]		0.016	[0.000, 0.038]		0.026	[0.001, 0.066]	*
Complexity	-0.008	[-0.033, 0.004]		-0.014	[-0.031, -0.003]	*	-0.010	[-0.030, 0.008]	
Environment Color	0.010	[-0.008, 0.042]		-0.004	[-0.018, 0.009]		-0.013	[-0.035, 0.002]	
Gist	0.017	[0.009, 0.050]	*	0.010	[-0.003, 0.025]		0.002	[-0.017, 0.024]	

Vibe	0.075	[0.092, 0.169]	*	0.001	[-0.020, 0.020]		-0.003	[-0.024, 0.017]	
Expressions × Facial Structure	-0.003	[-0.021, 0.007]		-0.002	[-0.013, 0.008]		-0.004	[-0.016, 0.005]	
Expressions × Gaze	0.018	[0.006, 0.058]	*	-0.003	[-0.020, 0.013]		-0.005	[-0.021, 0.011]	
Expressions × Skin Color	0.014	[0.002, 0.047]	*	0.005	[-0.008, 0.019]		0.010	[-0.003, 0.029]	
Expressions × Shape	0.014	[0.000, 0.047]		0.011	[0.000, 0.024]		0.006	[-0.005, 0.023]	
Expressions × Body Pose	0.008	[-0.010, 0.035]		-0.023	[-0.042, -0.008]	*	-0.003	[-0.016, 0.008]	
Expressions × Head Pose	0.011	[-0.001, 0.038]		0.018	[0.005, 0.036]	*	-0.002	[-0.014, 0.009]	
Expressions × Action	0.006	[-0.019, 0.038]		0.001	[-0.023, 0.020]		-0.005	[-0.021, 0.008]	
Expressions × Clothing Color	0.000	[-0.015, 0.016]		-0.009	[-0.020, 0.000]	*	-0.004	[-0.015, 0.003]	
Expressions × Clothing Style	-0.014	[-0.057, 0.006]		0.011	[-0.006, 0.028]		0.000	[-0.014, 0.013]	
Expressions × Hair Color	-0.013	[-0.044, -0.003]	*	0.001	[-0.010, 0.011]		0.003	[-0.015, 0.021]	
Expressions × Hair Style	0.007	[-0.010, 0.037]		-0.009	[-0.024, 0.005]		0.005	[-0.009, 0.021]	
Expressions × Complexity	0.000	[-0.018, 0.021]		-0.009	[-0.022, 0.003]		0.005	[-0.004, 0.016]	
Expressions × Environment Color	-0.002	[-0.023, 0.016]		-0.007	[-0.021, 0.005]		-0.004	[-0.014, 0.004]	
Expressions × Gist	-0.007	[-0.030, 0.007]		-0.003	[-0.015, 0.008]		0.009	[0.002, 0.021]	*
Expressions × Vibe	0.028	[0.020, 0.075]	*	0.009	[-0.005, 0.025]		0.002	[-0.014, 0.019]	
Facial Structure × Gaze	-0.001	[-0.012, 0.007]		-0.004	[-0.012, 0.003]		-0.002	[-0.011, 0.006]	
Facial Structure × Skin Color	-0.004	[-0.018, 0.003]		0.000	[-0.008, 0.008]		-0.011	[-0.028, -0.001]	*
Facial Structure × Shape	0.003	[-0.005, 0.014]		0.004	[-0.001, 0.010]		0.007	[-0.004, 0.022]	
Facial Structure × Body Pose	-0.003	[-0.017, 0.005]		-0.003	[-0.011, 0.004]		-0.006	[-0.018, 0.003]	
Facial Structure × Head Pose	0.002	[-0.007, 0.014]		0.001	[-0.005, 0.009]		-0.004	[-0.014, 0.006]	
Facial Structure × Action	-0.002	[-0.014, 0.007]		-0.003	[-0.011, 0.006]		-0.001	[-0.011, 0.011]	
Facial Structure × Clothing Color	0.001	[-0.005, 0.008]		-0.002	[-0.006, 0.003]		-0.001	[-0.008, 0.008]	
Facial Structure × Clothing Style	0.002	[-0.007, 0.017]		0.002	[-0.006, 0.011]		-0.008	[-0.023, 0.004]	
Facial Structure × Hair Color	0.002	[-0.008, 0.012]		0.000	[-0.004, 0.006]		0.031	[0.027, 0.055]	*
Facial Structure × Hair Style	-0.002	[-0.016, 0.008]		-0.004	[-0.013, 0.005]		-0.017	[-0.035, -0.006]	*
Facial Structure × Complexity	0.002	[-0.004, 0.011]		-0.002	[-0.007, 0.003]		0.000	[-0.008, 0.008]	
Facial Structure × Environment Color	0.001	[-0.011, 0.014]		-0.002	[-0.007, 0.004]		0.003	[-0.004, 0.012]	

Facial Structure × Gist	0.001	[-0.008, 0.006]		0.003	[0.001, 0.010]	*	0.001	[-0.004, 0.012]	
Facial Structure × Vibe	-0.004	[-0.019, 0.007]		-0.003	[-0.010, 0.004]		-0.009	[-0.022, -0.002]	*
Gaze × Skin Color	-0.003	[-0.021, 0.010]		-0.009	[-0.022, 0.002]		-0.007	[-0.023, 0.005]	
Gaze × Shape	-0.005	[-0.024, 0.007]		0.001	[-0.010, 0.011]		0.002	[-0.009, 0.013]	
Gaze × Body Pose	0.004	[-0.008, 0.025]		0.006	[-0.004, 0.017]		-0.007	[-0.020, 0.004]	
Gaze × Head Pose	0.006	[-0.009, 0.029]		0.004	[-0.008, 0.017]		0.009	[-0.005, 0.026]	
Gaze × Action	-0.011	[-0.038, 0.001]		0.012	[0.000, 0.029]	*	0.009	[-0.004, 0.026]	
Gaze × Clothing Color	-0.002	[-0.014, 0.009]		0.000	[-0.009, 0.008]		-0.004	[-0.015, 0.005]	
Gaze × Clothing Style	-0.003	[-0.022, 0.010]		-0.001	[-0.014, 0.011]		-0.006	[-0.022, 0.006]	
Gaze × Hair Color	0.004	[-0.005, 0.018]		0.001	[-0.006, 0.008]		0.000	[-0.017, 0.016]	
Gaze × Hair Style	0.000	[-0.013, 0.014]		-0.009	[-0.022, 0.002]		-0.002	[-0.017, 0.014]	
Gaze × Complexity	0.003	[-0.006, 0.017]		0.004	[-0.005, 0.012]		0.002	[-0.008, 0.012]	
Gaze × Environment Color	0.003	[-0.007, 0.017]		-0.008	[-0.019, 0.001]		0.000	[-0.009, 0.008]	
Gaze × Gist	0.000	[-0.011, 0.012]		-0.004	[-0.013, 0.002]		0.002	[-0.006, 0.011]	
Gaze × Vibe	-0.002	[-0.027, 0.020]		0.002	[-0.012, 0.015]		-0.004	[-0.016, 0.006]	
Skin Color × Shape	-0.007	[-0.026, 0.001]		-0.002	[-0.013, 0.008]		0.001	[-0.013, 0.014]	
Skin Color × Body Pose	-0.002	[-0.020, 0.012]		0.007	[-0.004, 0.021]		0.012	[0.001, 0.027]	*
Skin Color × Head Pose	0.003	[-0.007, 0.020]		0.007	[-0.003, 0.020]		-0.006	[-0.018, 0.004]	
Skin Color × Action	-0.001	[-0.020, 0.016]		-0.005	[-0.019, 0.009]		-0.005	[-0.020, 0.007]	
Skin Color × Clothing Color	0.001	[-0.010, 0.015]		0.002	[-0.010, 0.014]		0.001	[-0.012, 0.014]	
Skin Color × Clothing Style	0.000	[-0.016, 0.015]		-0.007	[-0.021, 0.006]		0.003	[-0.011, 0.019]	
Skin Color × Hair Color	-0.006	[-0.022, 0.002]		0.004	[-0.004, 0.013]		-0.052	[-0.084, -0.045]	*
Skin Color × Hair Style	-0.006	[-0.025, 0.006]		0.006	[-0.004, 0.017]		-0.004	[-0.024, 0.015]	
Skin Color × Complexity	-0.003	[-0.018, 0.006]		0.003	[-0.009, 0.016]		-0.001	[-0.012, 0.009]	
Skin Color × Environment Color	-0.002	[-0.014, 0.009]		-0.004	[-0.015, 0.008]		0.005	[-0.006, 0.018]	
Skin Color × Gist	-0.005	[-0.026, 0.008]		0.004	[-0.006, 0.014]		0.001	[-0.013, 0.014]	
Skin Color × Vibe	-0.012	[-0.042, 0.002]		-0.002	[-0.015, 0.012]		-0.002	[-0.014, 0.010]	
Shape × Body Pose	-0.019	[-0.051, -0.015]	*	0.000	[-0.011, 0.011]		0.000	[-0.021, 0.020]	

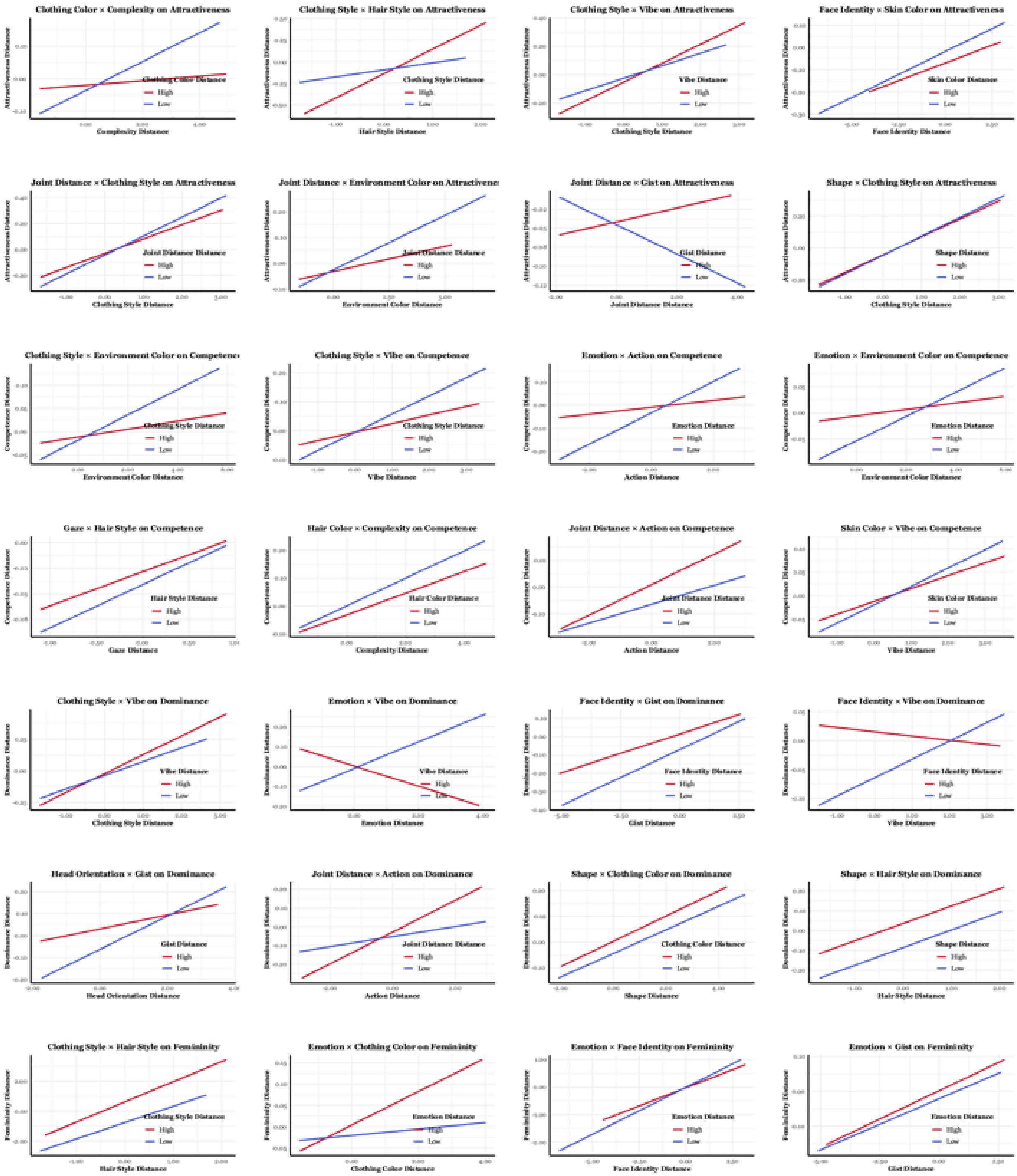
Shape × Head Pose	0.000	[-0.019, 0.019]		-0.001	[-0.013, 0.012]		-0.014	[-0.031, -0.004]	*
Shape × Action	-0.006	[-0.030, 0.010]		0.011	[0.001, 0.023]	*	-0.011	[-0.027, 0.002]	
Shape × Clothing Color	0.001	[-0.009, 0.013]		-0.002	[-0.009, 0.005]		0.003	[-0.007, 0.015]	
Shape × Clothing Style	0.003	[-0.010, 0.022]		-0.013	[-0.026, -0.004]	*	0.000	[-0.016, 0.015]	
Shape × Hair Color	-0.001	[-0.016, 0.013]		-0.002	[-0.008, 0.005]		0.003	[-0.017, 0.026]	
Shape × Hair Style	0.000	[-0.015, 0.013]		0.008	[-0.002, 0.020]		0.010	[-0.005, 0.031]	
Shape × Complexity	0.003	[-0.009, 0.019]		0.004	[-0.002, 0.012]		0.000	[-0.013, 0.012]	
Shape × Environment Color	0.007	[-0.012, 0.035]		0.002	[-0.006, 0.010]		0.002	[-0.009, 0.015]	
Shape × Gist	0.004	[-0.006, 0.016]		0.005	[-0.002, 0.014]		-0.008	[-0.021, 0.002]	
Shape × Vibe	0.007	[-0.011, 0.035]		0.009	[0.000, 0.020]		-0.002	[-0.013, 0.009]	
Body Pose × Head Pose	0.004	[-0.012, 0.024]		0.001	[-0.012, 0.015]		0.006	[-0.009, 0.026]	
Body Pose × Action	0.000	[-0.020, 0.021]		-0.009	[-0.023, 0.001]		-0.005	[-0.020, 0.009]	
Body Pose × Clothing Color	0.006	[-0.001, 0.022]		-0.007	[-0.015, 0.000]	*	0.002	[-0.007, 0.012]	
Body Pose × Clothing Style	-0.005	[-0.024, 0.009]		0.006	[-0.005, 0.018]		-0.003	[-0.017, 0.010]	
Body Pose × Hair Color	-0.001	[-0.014, 0.011]		-0.002	[-0.009, 0.005]		-0.007	[-0.027, 0.009]	
Body Pose × Hair Style	-0.003	[-0.021, 0.010]		-0.007	[-0.020, 0.004]		0.000	[-0.017, 0.016]	
Body Pose × Complexity	-0.004	[-0.020, 0.006]		-0.003	[-0.013, 0.007]		0.002	[-0.009, 0.013]	
Body Pose × Environment Color	-0.001	[-0.018, 0.015]		0.003	[-0.005, 0.012]		0.000	[-0.010, 0.010]	
Body Pose × Gist	0.000	[-0.013, 0.012]		-0.002	[-0.011, 0.006]		0.008	[0.001, 0.020]	*
Body Pose × Vibe	0.008	[-0.011, 0.038]		0.003	[-0.011, 0.018]		0.000	[-0.014, 0.013]	
Head Pose × Action	0.003	[-0.011, 0.023]		-0.017	[-0.033, -0.004]	*	0.010	[0.000, 0.026]	
Head Pose × Clothing Color	0.003	[-0.009, 0.019]		-0.002	[-0.010, 0.007]		-0.006	[-0.017, 0.003]	
Head Pose × Clothing Style	-0.014	[-0.040, -0.010]	*	-0.010	[-0.024, 0.002]		0.002	[-0.013, 0.018]	
Head Pose × Hair Color	0.000	[-0.015, 0.013]		0.000	[-0.008, 0.007]		-0.004	[-0.027, 0.017]	
Head Pose × Hair Style	0.007	[0.000, 0.027]	*	0.004	[-0.008, 0.017]		-0.002	[-0.020, 0.015]	
Head Pose × Complexity	0.003	[-0.007, 0.018]		0.008	[0.000, 0.018]		0.002	[-0.006, 0.012]	
Head Pose × Environment Color	0.004	[-0.006, 0.019]		0.004	[-0.004, 0.015]		0.008	[0.001, 0.020]	*
Head Pose × Gist	-0.001	[-0.013, 0.009]		-0.001	[-0.008, 0.008]		-0.005	[-0.015, 0.003]	

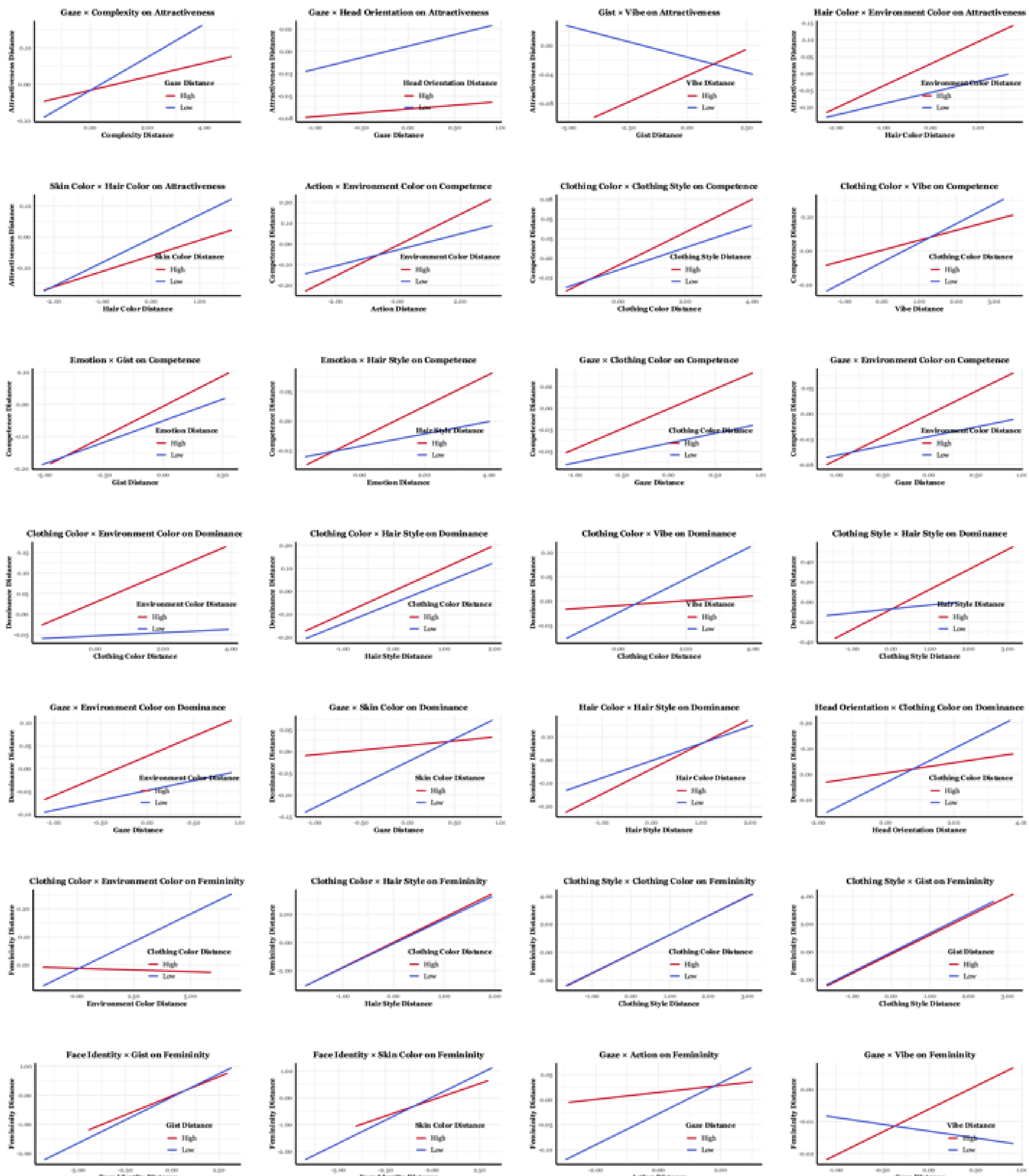
Head Pose × Vibe	0.004	[-0.018, 0.033]		-0.002	[-0.014, 0.011]		0.006	[-0.003, 0.019]	
Action × Clothing Color	-0.010	[-0.028, -0.006]	*	-0.003	[-0.012, 0.006]		0.002	[-0.009, 0.014]	
Action × Clothing Style	0.001	[-0.018, 0.020]		-0.009	[-0.025, 0.004]		0.024	[0.014, 0.048]	*
Action × Hair Color	0.002	[-0.009, 0.015]		0.000	[-0.006, 0.007]		0.013	[-0.003, 0.035]	
Action × Hair Style	0.004	[-0.007, 0.023]		0.012	[0.001, 0.027]	*	-0.006	[-0.029, 0.010]	
Action × Complexity	-0.003	[-0.017, 0.009]		-0.002	[-0.013, 0.007]		0.004	[-0.006, 0.014]	
Action × Environment Color	0.005	[-0.007, 0.025]		0.005	[-0.005, 0.015]		0.002	[-0.009, 0.014]	
Action × Gist	-0.004	[-0.017, 0.005]		0.007	[0.000, 0.016]		-0.002	[-0.012, 0.008]	
Action × Vibe	0.008	[-0.014, 0.043]		-0.007	[-0.026, 0.008]		0.007	[-0.004, 0.021]	
Clothing Color × Clothing Style	0.002	[-0.010, 0.018]		-0.001	[-0.010, 0.007]		0.001	[-0.013, 0.016]	
Clothing Color × Hair Color	0.000	[-0.007, 0.008]		0.003	[-0.003, 0.009]		0.005	[-0.009, 0.023]	
Clothing Color × Hair Style	0.002	[-0.007, 0.014]		0.006	[-0.001, 0.015]		-0.004	[-0.020, 0.009]	
Clothing Color × Complexity	0.004	[0.000, 0.015]		0.006	[0.000, 0.014]		0.005	[-0.003, 0.016]	
Clothing Color × Environment Color	0.001	[-0.009, 0.012]		-0.005	[-0.013, 0.001]		-0.003	[-0.012, 0.004]	
Clothing Color × Gist	-0.001	[-0.011, 0.006]		0.000	[-0.006, 0.007]		-0.003	[-0.013, 0.005]	
Clothing Color × Vibe	0.004	[-0.008, 0.023]		0.005	[-0.005, 0.015]		0.002	[-0.007, 0.013]	
Clothing Style × Hair Color	-0.011	[-0.037, -0.005]	*	0.002	[-0.009, 0.014]		-0.015	[-0.045, 0.003]	
Clothing Style × Hair Style	-0.014	[-0.041, -0.007]	*	-0.010	[-0.023, 0.001]		0.026	[0.016, 0.049]	*
Clothing Style × Complexity	-0.006	[-0.027, 0.004]		0.005	[-0.002, 0.015]		-0.004	[-0.018, 0.008]	
Clothing Style × Environment Color	-0.007	[-0.030, 0.007]		0.005	[-0.004, 0.016]		-0.003	[-0.018, 0.012]	
Clothing Style × Gist	-0.006	[-0.025, 0.005]		-0.001	[-0.011, 0.008]		-0.003	[-0.018, 0.010]	
Clothing Style × Vibe	0.016	[0.007, 0.053]	*	-0.001	[-0.014, 0.013]		0.007	[-0.005, 0.022]	
Hair Color × Hair Style	0.009	[0.000, 0.033]	*	-0.008	[-0.022, 0.003]		0.019	[0.003, 0.047]	*
Hair Color × Complexity	0.002	[-0.005, 0.013]		-0.002	[-0.007, 0.004]		-0.009	[-0.026, 0.005]	
Hair Color × Environment Color	-0.001	[-0.012, 0.008]		0.000	[-0.005, 0.006]		0.012	[-0.001, 0.030]	
Hair Color × Gist	-0.002	[-0.013, 0.005]		-0.005	[-0.011, 0.000]		-0.015	[-0.034, -0.002]	*
Hair Color × Vibe	0.007	[-0.001, 0.026]		0.002	[-0.006, 0.010]		-0.012	[-0.033, 0.003]	

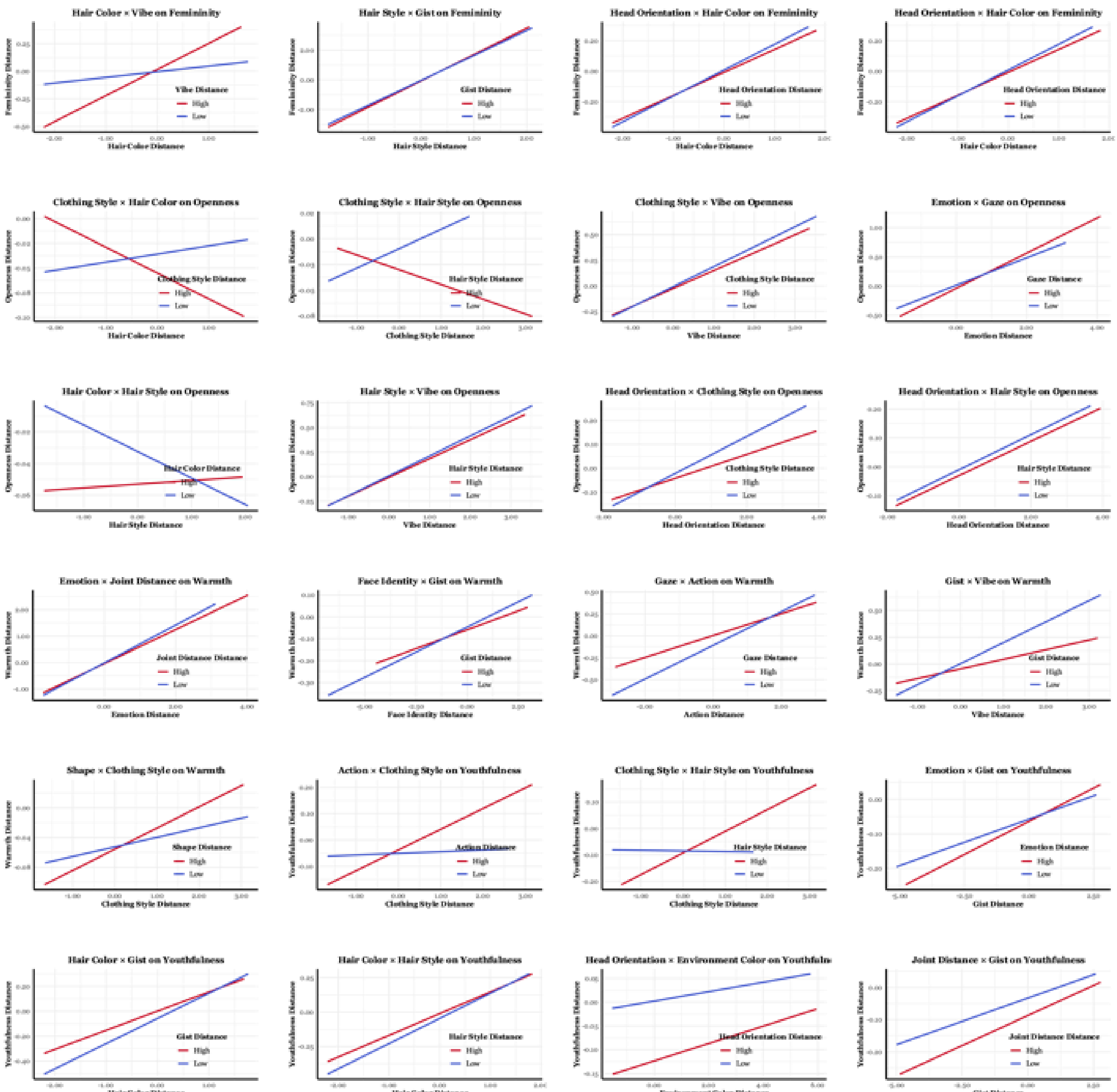
Hair Style × Complexity	0.004	[-0.005, 0.020]		0.000	[-0.009, 0.008]		0.000	[-0.016, 0.015]	
Hair Style × Environment Color	0.008	[-0.001, 0.028]		-0.001	[-0.011, 0.007]		0.004	[-0.011, 0.019]	
Hair Style × Gist	0.000	[-0.012, 0.012]		0.006	[-0.002, 0.015]		-0.003	[-0.017, 0.010]	
Hair Style × Vibe	-0.014	[-0.044, -0.005]	*	0.012	[0.001, 0.027]	*	0.002	[-0.015, 0.019]	
Complexity × Environment Color	0.006	[-0.002, 0.022]		-0.003	[-0.009, 0.004]		-0.004	[-0.014, 0.005]	
Complexity × Gist	0.005	[-0.003, 0.019]		0.000	[-0.009, 0.010]		-0.006	[-0.018, 0.004]	
Complexity × Vibe	-0.006	[-0.028, 0.007]		-0.003	[-0.014, 0.009]		-0.002	[-0.012, 0.007]	
Environment Color × Gist	0.003	[-0.007, 0.015]		-0.003	[-0.011, 0.003]		0.002	[-0.007, 0.012]	
Environment Color × Vibe	0.019	[0.014, 0.053]	*	0.007	[-0.003, 0.018]		0.004	[-0.006, 0.015]	
Gist × Vibe	0.007	[-0.007, 0.030]		-0.012	[-0.025, -0.003]	*	-0.007	[-0.019, 0.002]	

Note. Each model regressed the distances in each trait impression on the distances in each of the 16 fine-grained cues and all pairwise two-way interactions between them across image pairs (N = 632,250) using representational similarity analysis with Ridge regression and cross-validation to increase generalizability. Effect size β indicates the standardized coefficient in the model (both the dependent variables and the independent variables in all pre-registered analyses were standardized). The significance of these effect sizes was estimated using bootstrap resampling as pre-registered where each bootstrap iteration selects a new set of images with replacement and computes their distances. The 95% confidence interval indicates the effect sizes fall within the 2.5% and 97.5% of the effect sizes across the 2000 bootstrap iterations. The significance, sig, indicates whether the lower-bound of this 95% confidence interval overlaps with zero. Statistically significant effects were indicated with asterisks.

Supplementary Figures




Gaze × Complexity on Attractiveness
Attractiveness Distance
Complexity Distance
Gaze Distance
High
Low
Gaze × Head Orientation on Attractiveness
Attractiveness Distance
Gaze Distance
Head Orientation Distance
High
Low
Gist × Vibe on Attractiveness
Attractiveness Distance
Gist Distance
Vibe Distance
High
Low
Hair Color × Environment Color on Attractiveness
Attractiveness Distance
Hair Color Distance
Environment Color Distance
High
Low
Skin Color × Hair Color on Attractiveness
Attractiveness Distance
Hair Color Distance
Skin Color Distance
High
Low
Action × Environment Color on Competence
Competence Distance
Action Distance
Environment Color Distance
High
Low
Clothing Color × Clothing Style on Competence
Competence Distance
Clothing Color Distance
Clothing Style Distance
High
Low
Clothing Color × Vibe on Competence
Competence Distance
Vibe Distance
Clothing Color Distance
High
Low
Emotion × Gist on Competence
Competence Distance
Gist Distance
Emotion Distance
High
Low
Emotion × Hair Style on Competence
Competence Distance
Emotion Distance
Hair Style Distance
High
Low
Gaze × Clothing Color on Competence
Competence Distance
Gaze Distance
Clothing Color Distance
High
Low
Gaze × Environment Color on Competence
Competence Distance
Gaze Distance
Environment Color Distance
High
Low
Clothing Color × Environment Color on Dominance
Dominance Distance
Clothing Color Distance
Environment Color Distance
High
Low
Clothing Color × Hair Style on Dominance
Dominance Distance
Hair Style Distance
Clothing Color Distance
High
Low
Clothing Color × Vibe on Dominance
Dominance Distance
Clothing Color Distance
Vibe Distance
High
Low
Clothing Style × Hair Style on Dominance
Dominance Distance
Clothing Style Distance
Hair Style Distance
High
Low
Gaze × Environment Color on Dominance
Dominance Distance
Gaze Distance
Environment Color Distance
High
Low
Gaze × Skin Color on Dominance
Dominance Distance
Gaze Distance
Skin Color Distance
High
Low
Hair Color × Hair Style on Dominance
Dominance Distance
Hair Style Distance
Hair Color Distance
High
Low
Head Orientation × Clothing Color on Dominance
Dominance Distance
Head Orientation Distance
Clothing Color Distance
High
Low
Clothing Color × Environment Color on Femininity
Femininity Distance
Environment Color Distance
Clothing Color Distance
High
Low
Clothing Color × Hair Style on Femininity
Femininity Distance
Hair Style Distance
Clothing Color Distance
High
Low
Clothing Style × Clothing Color on Femininity
Femininity Distance
Clothing Style Distance
Clothing Color Distance
High
Low
Clothing Style × Gist on Femininity
Femininity Distance
Clothing Style Distance
Gist Distance
High
Low
Face Identity × Gist on Femininity
Femininity Distance
Face Identity Distance
Gist Distance
High
Low
Face Identity × Skin Color on Femininity
Femininity Distance
Face Identity Distance
Skin Color Distance
High
Low
Gaze × Action on Femininity
Femininity Distance
Action Distance
Gaze Distance
High
Low
Gaze × Vibe on Femininity
Femininity Distance
Gaze Distance
Vibe Distance
High
Low



Hair Color × Vibe on Femininity
Femininity Distance
Hair Color Distance
Vibe Distance
High
Low
Hair Style × Gist on Femininity
Femininity Distance
Hair Style Distance
Gist Distance
High
Low
Head Orientation × Hair Color on Femininity
Femininity Distance
Hair Color Distance
Head Orientation Distance
High
Low
Head Orientation × Hair Color on Femininity
Femininity Distance
Hair Color Distance
Head Orientation Distance
High
Low
Clothing Style × Hair Color on Openness
Openness Distance
Hair Color Distance
Clothing Style Distance
High
Low
Clothing Style × Hair Style on Openness
Openness Distance
Clothing Style Distance
Hair Style Distance
High
Low
Clothing Style × Vibe on Openness
Openness Distance
Vibe Distance
Clothing Style Distance
High
Low
Emotion × Gaze on Openness
Openness Distance
Emotion Distance
Gaze Distance
High
Low
Hair Color × Hair Style on Openness
Openness Distance
Hair Style Distance
Hair Color Distance
High
Low
Hair Style × Vibe on Openness
Openness Distance
Vibe Distance
Hair Style Distance
High
Low
Head Orientation × Clothing Style on Openness
Openness Distance
Head Orientation Distance
Clothing Style Distance
High
Low
Head Orientation × Hair Style on Openness
Openness Distance
Head Orientation Distance
Hair Style Distance
High
Low
Emotion × Joint Distance on Warmth
Warmth Distance
Emotion Distance
Joint Distance Distance
High
Low
Face Identity × Gist on Warmth
Warmth Distance
Face Identity Distance
Gist Distance
High
Low
Gaze × Action on Warmth
Warmth Distance
Action Distance
Gaze Distance
High
Low
Gist × Vibe on Warmth
Warmth Distance
Vibe Distance
Gist Distance
High
Low
Shape × Clothing Style on Warmth
Warmth Distance
Clothing Style Distance
Shape Distance
High
Low
Action × Clothing Style on Youthfulness
Youthfulness Distance
Clothing Style Distance
Action Distance
High
Low
Clothing Style × Hair Style on Youthfulness
Youthfulness Distance
Clothing Style Distance
Hair Style Distance
High
Low
Emotion × Gist on Youthfulness
Youthfulness Distance
Gist Distance
Emotion Distance
High
Low
Hair Color × Gist on Youthfulness
Youthfulness Distance
Hair Color Distance
Gist Distance
High
Low
Hair Color × Hair Style on Youthfulness
Youthfulness Distance
Hair Color Distance
Hair Style Distance
High
Low
Head Orientation × Environment Color on Youthfulness
Youthfulness Distance
Environment Color Distance
Head Orientation Distance
High
Low
Joint Distance × Gist on Youthfulness
Youthfulness Distance
Gist Distance
Joint Distance Distance
High
Low

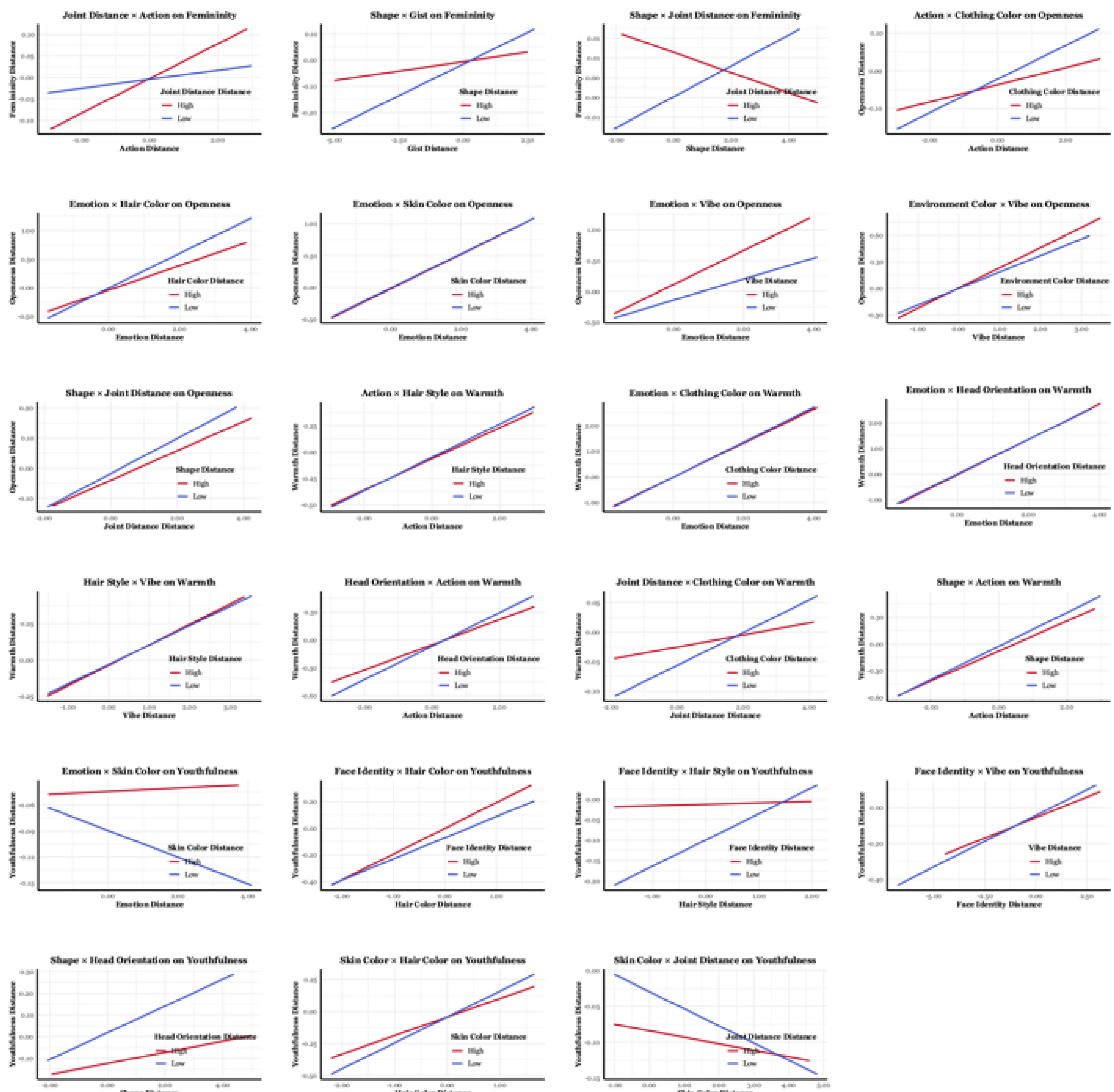


Fig. S1. Interactions between Fine-grained Cues on Each Trait Impression. Each panel plots a statistically significant interaction effect between two fine-grained cues on a trait impression according to the pre-registered interaction analysis with representational similarity analysis and Ridge regression with cross-validation. To visualize these interaction effects, we split one of the cues into high distances (red lines), median distances, and low distances (blue lines) and plotted for the high-distance and low-distance groups the Pearson correlations between the distances in another cue (x-axes) and the distances in a trait impression (y-axes).