PNAS Nexus, 2024, **3**, 1–15

https://doi.org/10.1093/pnasnexus/pgae066
Advance access publication 5 March 2024
Research Report

Predicting individual differences in peak emotional response

Felix Schoeller[a,b,*,1], Leonardo Christov-Moore[a,1], Caitlin Lynch[a], Thomas Diot[c] and Nicco Reggente[a]

[a]Institute for Advanced Consciousness Studies, Santa Monica, CA 90403, USA
[b]Media Lab, Massachusetts Institute of Technology, Cambridge, MA 02139, USA
[c]Department of Psychiatry, GHU Paris Psychiatrie et Neurosciences, Paris 75010, France
*To whom correspondence should be addressed: Email: felix@advancedconsciousness.org
[1]F.S. and L.C.-M. contributed equally to this work.
Edited By: Paulo Boggio

Abstract

Why does the same experience elicit strong emotional responses in some individuals while leaving others largely indifferent? Is the variance influenced by who people are (personality traits), how they feel (emotional state), where they come from (demographics), or a unique combination of these? In this 2,900+ participants study, we disentangle the factors that underlie individual variations in the universal experience of aesthetic chills, the feeling of cold and shivers down the spine during peak experiences. Here, we unravel the interplay of psychological and sociocultural dynamics influencing self-reported chills reactions. A novel technique harnessing mass data mining of social media platforms curates the first large database of ecologically sourced chills-evoking stimuli. A combination of machine learning techniques (LASSO and SVM) and multilevel modeling analysis elucidates the interacting roles of demographics, traits, and states factors in the experience of aesthetic chills. These findings highlight a tractable set of features predicting the occurrence and intensity of chills—age, sex, pre-exposure arousal, predisposition to Kama Muta (KAMF), and absorption (modified tellegen absorption scale [MODTAS]), with 73.5% accuracy in predicting the occurrence of chills and accounting for 48% of the variance in chills intensity. While traditional methods typically suffer from a lack of control over the stimuli and their effects, this approach allows for the assignment of stimuli tailored to individual biopsychosocial profiles, thereby, increasing experimental control and decreasing unexplained variability. Further, they elucidate how hidden sociocultural factors, psychological traits, and contextual states shape seemingly "subjective" phenomena.

Keywords: aesthetic chills, machine learning, absorption, positive affect exposure, individual differences

Significance Statement

The study leverages an innovative combination of social media mining and machine learning to provide major insights into the factors shaping aesthetic chills—a universal yet highly variable emotional experience. Using a large database of real-world aesthetic stimuli and modeling data from over 2,900 participants, we demonstrate the interacting roles of age, sex, emotional state, personality traits, and cultural exposure in predicting both the occurrence and intensity of chills. These findings have important implications for understanding how universal emotional experiences are shaped by a combination of psychological, demographic, and cultural variables. Given the recognized therapeutic benefits of positive emotion, these data-driven insights represent a significant step towards developing personalized adjunct treatments that could improve outcomes for multiple affective disorders.

Introduction

We have all experienced it—sharing a joke, a movie scene, or an inspirational speech with a friend, expecting it to move them as profoundly as it moved us, only to be met with a lukewarm reaction. "Beauty is in the eye of the beholder," they say. But what accounts for such vastly different reactions to the same stimulus? Are some innately more prone to being moved than others? How do factors like personality and upbringing shape our susceptibility? Though methodologically daunting, disentangling the complex factors underlying these individual differences is key to harnessing the therapeutic promise of peak emotional experiences (1–5). One such universal peak experience is aesthetic chills (henceforth "chills")—an intense psychophysiological response to specific rewarding or aversive stimuli associated with shivers, goosebumps, and a feeling of cold down the neck

Competing Interest: F.S., L.C.-M., C.L., and N.R. are all supported by Tiny Blue Dot Foundation and the Mordechai Walder Charitable Fund. F.S. is partially funded by a Joy Ventures research grant. In the past years, F.S. has been funded and received compensation from BeSound SAS and Nested Minds LTD. In addition, F.S. work has been funded by the European Commission and the French Ministry of Armed Forces (AID). T.D. declares that he has no competing interest.
Received: October 19, 2023. **Accepted:** January 24, 2024

and/or spine (6–12). Here chills serve as a somatic marker for peak emotional experiences (13–19)—i.e. bodily sensations that act as emotional, conditioned responses representing complex reinforcer values related to prior experiences (7, 20). Chills have been a research topic of growing interest in the past decade (7, 21), notably for their effects on positive affect (22, 23), reward learning (6, 13, 22, 24), memory and attentional processes (25, 26), prosocial tendencies (27–29), and as a nonpharmacological substitute for dopaminergic-related illnesses, and mood disorders (4, 7, 22). Substantial individual differences exist in both propensity for and intensity of chills (24, 30–40), which hinders progress in understanding and utilizing chills as therapeutic tools for mental health conditions and enhancing positive emotional experiences broadly.

Here, we leverage a large cohort (N = 2,937) and a robust, multimethod approach to disentangle the influences of demographics, traits, and stimulus on chills likelihood and intensity. Participants completed validated measures assessing demographics, personality, and emotional state before exposure to musical and audiovisual stimuli (see Fig. 1), which were empirically confirmed across large samples to elicit chills beforehand in the population of interest (41, 42). Advances in data science have revolutionized the scientific study of subjective phenomena by permitting the analysis of massive datasets of publicly available naturalistic reactions to stimuli provided by social media (43, 44). Here, we used a novel technique leveraging online social platforms and crowdsourcing to curate and empirically validate a stimulus set for eliciting aesthetic chills. Through developing natural language processing algorithms that data mine YouTube and Reddit comments for somatic markers of chills and goosebumps, we extracted 40 emotion-evoking audiovisual clips collectively identified by users to produce shivers (41, 42).

To disentangle the multifactorial influences shaping self-reported chills, we followed a multilevel statistical approach. First, we used univariate analyses to establish baseline demographic and contextual differences (a.k.a., states) between those who report chills vs. those who do not. Subsequently, we used multivariate regression to model trait predictors of chills reactions. We then performed latent class analysis (LCA) to reveal hidden "cultures" reflecting sociocultural response patterns after accounting for stimuli, states, and trait effects (Fig. 1 and Table 1). This approach is effective for characterizing the dataset and identifying clusters of subjects who are more prone to experience chills or more intense chills. However, it does not have predictive value on its own. For this purpose, we leveraged machine learning techniques with the goal to move toward providing researchers interested in chills with an instrument that would allow them to administer the right stimuli at the right time to the right person, and thereby allow operationalized control of the emotion in experimental settings.

Accordingly, in order to assess the ecological validity of using individual characteristics to predict the occurrence of chills in response to audiovisual stimuli, we leveraged machine learning within a cross-validation framework to predict both the chills occurrence (binary; support vector machine [SVM] approach) and chills intensity (continuous; least absolute shrinkage, and selection operator [LASSO] approach). These approaches not only yield an assessment of predictive power but also identify the most parsimonious combination of demographic, psychological, and contextual factors that constitute an informative feature set for predicting response in unseen individuals.

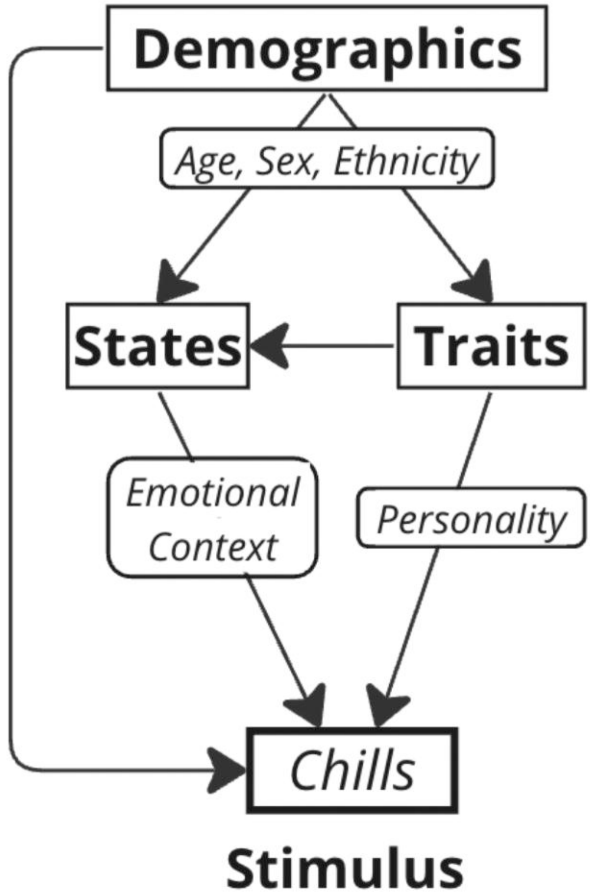

Fig. 1. The interplay of demographics, traits, and states predict the occurrence of aesthetic chills in response to chills stimuli. Each scale represents distinct layers of influence on the individual's chills response. Demographics encompass age, education, gender, and political orientation. Traits include personality aspects like extraversion, conscientiousness, and absorption. States denote emotional factors like valence and arousal.

The true value of models related to human emotions lies not only in their ability to describe but also in their potential to reduce uncertainty about future emotional responses. If a person's characteristics, current state, and demographic information indeed influence their emotional reactions to stimuli, then having this information before exposure to the stimuli should allow for accurate predictions about their responses. Successfully implementing this approach could enable personalized content curation aimed at maximizing the likelihood of eliciting chills, which holds significant implications for both research and clinical applications. We hypothesized that individuals who score higher on measures of openness to experience, absorption, and dispositional positive emotions would report more frequent and intense experiences of chills in response to validated audiovisual stimuli compared to individuals scoring lower on these measures. Specifically, we predicted that participants' scores on the NEO-FFI Openness domain, the modified tellegen absorption scale (MODTAS), and the dispositional positive emotions scale (DPES) would show significant positive correlations with both the likelihood of experiencing chills and the self-reported intensity of chills experiences across stimuli.

Table 1. Summary of statistical models used in the analysis.

Model type and goal	Dependent variable	Independent variables	Technical details
Step 1: Characterization of the dataset			
Univariate logistic regression: Isolate demographic impact on chills experience	Likelihood of aesthetic chills	Stimuli-related factors (video ID)	Univariate logistic regression was conducted to assess associations, calculating unadjusted ORs with 95% confidence intervals (95% CIs)
Univariate mixed-effects logistic regression: Assess demographics and psychological traits' impact on chills	Likelihood of aesthetic chills	Random effect: stimuli-related factors (video ID) Fixed effect: demographic factors (age, gender, ethnicity) and psychological traits (NEO-FFI, MODTAS, DPES, KAMF)	Variables with $P < 0.2$ from univariate analysis were included in multivariate analysis using a stepwise bidirectional procedure based on the AIC
Multivariate logistic regression: Assess simultaneously demographics and psychological traits" impact on chills	Likelihood of aesthetic chills	Random effect: stimuli-related factors (video ID) Fixed effect: demographic factors (age, gender, ethnicity) and psychological traits (NEO-FFI, MODTAS, DPES, KAMF)	Assessed linearity, independence, multicollinearity; significant at $P < 0.01$
LCA: Discover underlying sociocultural patterns	Identification of cultural DNA	Sociodemographic data (age, gender, education, ethnicity, political preferences)	The optimal number of latent classes was determined based on statistical properties (AIC), when model convergence has been achieved (with a maximum number of iterations allowed of 10 millions)
Step 2: Machine learning and cross-validation			
LASSO cross-validation: determine the predictive power of features on chills intensity	Chills intensity (continuous)	Combination of demographic, psychological, and stimuli-related factors	λ optimization on $n-1$ cross-validation to minimize RMSE, leave-25%-out-cross-validation; 10 k iterations; significant at $P < 0.01$
SVM: Determine the predictive power of features on chills occurrence	Chills occurrence (binary)	Combination of demographic, psychological, and stimuli-related factors	Radial basis function kernel, $c = 1$; balanced classes, leave-25%-out-cross-validation; 10k iterations; significant at $P < 0.01$

This table delineates the types of regression models employed in the study, outlining the dependent and independent variables associated with each model. It begins with univariate logistic regression, focusing on demographic factors, and progresses through more complex models, eventually integrating psychological traits, and sociodemographic data. The final stage, LASSO regression and SVM cross-validations, assesses the identification, and predictive power of parsimonious feature sets.

Materials and methods

Experimental design

The study employs a cross-sectional correlational research design to comprehensively investigate the underlying factors influencing individual variability in the experience of aesthetic chills. Its primary objective is to unveil the intricate interplay of psychological and sociocultural dynamics in shaping chills reactions in a diverse cohort of $N \asymp 3{,}000$ participants from Southern California. Through a multimethod approach, validated scales assessing demographics, personality traits, emotional tendencies, and psychological characteristics are administered to participants. Subsequently, participants are exposed to a validated set of 40 emotion-evoking audiovisual stimuli. The study employs a two-step combination of categorical and continuous data analysis techniques, including (i) univariate and multivariate regression, LCA, and (ii) LASSO regression, and SVM (see the Statistical methods section) within a cross-validation framework. These analyses collectively enable the exploration of relationships between demographics, personality, and context and the likelihood of experiencing chills. The study's cross-sectional nature enables the identification of associations without manipulating variables, contributing to a comprehensive understanding of the complex interplay between psychological traits and sociocultural influences in shaping the subjective experience of aesthetic chills.

Procedure

Participants were recruited for this study through an online platform (Qualtrics.com) with a focus on individuals residing in Southern California. Before proceeding with the study, participants underwent an initial screening to confirm their geographical location and provide their informed consent. Participants were then asked to provide demographic information including gender, education level, and age. Additionally, participants were queried about their political orientation and whether they were affiliated with any political party. In order to assess participants' emotional state, they were prompted to indicate their levels of valence and arousal. Subsequently, participants completed several questionnaires including the disposition positive affect (DPES), NEO five-factor inventory (NEO-FFI), MODTAS, and Kama Muta questionnaire (KAMF). Participants were then pseudorandomly assigned to one of 40 stimuli. After exposure to the randomly assigned stimulus, participants were asked to report their emotional state in terms of valence and arousal once again. They were also asked to indicate their level of liking for the video, whether they had seen the video previously, whether they experienced chills while watching the video, and if so, to rate the frequency and intensity of their chills. Participants were also asked whether the video reminded them of a personal experience, and if they experienced goosebumps or tears, they were asked to indicate what elicited those responses. Upon completion of the study, participants were thanked for their participation and provided with appropriate remuneration for their time and effort. The average duration of each experiment was ~37 min.

Participants

A total of 3,259 participants initially took part in the experiment. Following data cleanup (see details in supplementary material), the experiment involved a diverse group of 2,937 participants, all of whom hailed from Southern California. The gender distribution was fairly balanced, with 54.24% identifying as female and 41.44% as male. In terms of political affiliation, the largest group identified as Democrats (50.66%), followed by Republicans (21.59%), and Independents (14.81%). Notably, 11.64% of participants did not specify a political affiliation, while a small proportion (1.19%) identified with other political affiliations. In regards to racial identity, the majority of participants (68.44%) identified as White or Caucasian. The second largest racial group was those identifying as other (11.37%), followed by American Indian/Native American or Alaska Native (4.97%), and Black or African American (1.46%). A small percentage of participants (0.31%) identified as Asian. Given this broad demographic range, this dataset provides a rich, representative sample for examining the phenomena under investigation in the context of Southern California.

Instruments

The DPES (45) measures one's dispositional tendencies to feel positive emotions towards others in their daily lives. The DPES consists of seven subscales, including joy, contentment, pride, love, compassion, amusement, and awe. The scale comprises a total of 38 items, with each subscale containing five or six items. Participants rate their agreement with statements such as "On a typical day, many events make me happy" on a seven-point Likert scale ranging from "1—strongly disagree" to "7—strongly agree." The total score is obtained by averaging the item responses, yielding a range from 1 to 7, with higher scores indicating greater levels of positive emotion.

The NEO five-factor inventory (NEO-FFI-3) (46) is a widely used personality assessment tool based on the five-factor model (FFM) of personality. It is designed to measure five broad dimensions of personality: neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness. The NEO-FFI-3 consists of 60 items, with 12 items for each of the five personality factors. Participants respond to statements such as "I worry a lot" or "I am talkative" on a Likert-type scale, indicating the extent to which each statement reflects their own personality traits. The NEO-FFI-3 provides researchers and practitioners with a concise and reliable measure of the key dimensions of personality, allowing for a comprehensive understanding of individuals' typical patterns of behavior, emotions, and cognition. The constituent items of NEO-FFI include negative affect, self-reproach, positive affect, sociability, activity, aesthetic interests, intellectual interests, unconventionality, nonantagonistic orientation, prosocial orientation, orderliness, goal-striving, and dependability.

The MODTAS (47) is a 34-item multidimensional measure that assesses imaginative involvement and the tendency to become mentally absorbed in everyday activities (48). We employed a modified version, the MODTAS (47), which has a Likert-scaled response format. Subjects are asked to rate the frequency of their experiences on a five-point scale, ranging from 0 (never) to 4 (very often). MODTAS has been found to have a clearer covariance structure than the original tellegen absorption scale (TAS). It consists of five correlated primary factors: synesthesia, altered states of consciousness, aesthetic involvement in nature, imaginative involvement, and apparent experiences of extra-sensory perception.

The KAMF (49–51) is a seven items scale measures predisposition for Kama Muta (Sanskrit, meaning: "moved by love") an emotion described as "being moved," "heart-warming," "stirring," or "being emotionally touched." It is a primarily positive emotion that is experienced as a feeling of buoyancy, security, and warmth in the chest, and may be accompanied by goosebumps or tears.

Stimuli

A crowdsourced database of chills-eliciting stimuli was constructed as a specialized open-access database tailored to the goals of this study (41). Leveraging online social media platforms, including YouTube and Reddit, a Python-based tool was developed to curate a collection of stimuli with the potential to elicit aesthetic chills. A breadth-first search algorithm (52) navigated the platforms, using a predefined dictionary of somatic markers such as "frisson," "chill," "goosebump," and "gooseflesh" to identify these markers within user comments. Only videos with over 100 comments and at least 10 occurrences of these markers were deemed suitable for inclusion. This process resulted in the acquisition of 204 potential stimuli, of which the top 50, based on the highest somatic marker frequency, were selected for further analysis. Online validation was conducted with over 3,500+ participants, involving recruitment from Prolific, Qualtrics, and an online interface with embedded attention checks to ensure data quality. Ultimately, this systematic approach yielded a curated set of 40 stimuli, equally divided between audio and audiovisual formats (see details in Ref. (41)).

Statistical methods

We employed a two-step comprehensive, stepwise approach to identify the factors influencing aesthetic chills (see Table 1 for overview). The progression ensures we accurately isolate specific influences like psychological traits or stimulus types, thereby avoiding confounding effects such as mistakenly attributing chills to general emotional responses instead of specific stimuli characteristics.

Step 1: Characterization of aesthetic chills: (i) We start with univariate logistic regression to individually examine the impact of stimuli-related variables on the likelihood of aesthetic chills. This is followed by a mixed-effects logistic regression, where we examine the effects of specific stimuli, treating each video ID as a random factor to account for within-stimuli variability. (ii) Next, multivariate logistic regression, integrates psychological traits, allowing us to explore how these traits interact with other variables in influencing chills. (iii) We then apply LCA to identify underlying patterns in sociodemographic data, seeking to reveal hidden sociocultural influences.

Step 2: Predictive modeling: Following this characterization of demographic, psychological, and sociocultural of chills, we employed machine learning and cross-validation techniques to ascertain the most parsimonious set of variables that yield ecologically valid predictive power. We used (i) SVM to predict the occurrence of aesthetic chills (binary classification: yes or no) and (ii) a LASSO regression to predict the intensity of experienced aesthetic chills (continuous classification: intensity between 0 and 100).

Step 1: characterization of aesthetic chills: demographic, psychological, and sociocultural correlates

1. Isolating the influence of demographic factors on chills experience: The first step in our analytical process aimed to isolate the influence of demographic variables on the likelihood of experiencing aesthetic chills. To do this, we employed univariate mixed-effect logistic regression. Previous studies on these stimuli have demonstrated a strong response

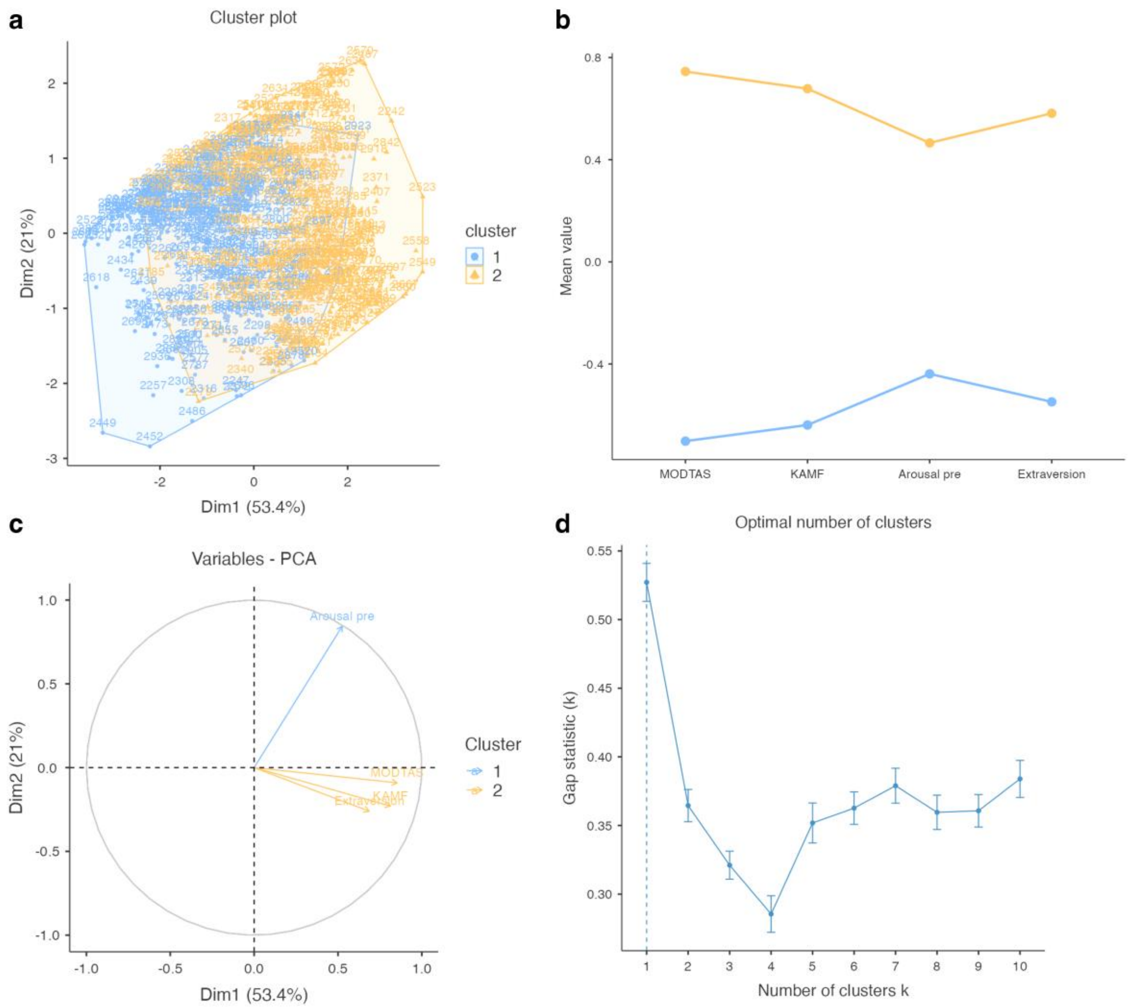

Fig. 2. Clustering of beta coefficients across pre-stimulus logistic regression analyses of most predictive traits against chills likelihood (a-d). Absorption (MODTAS) and prestimulus arousal seem to differentially drive chills likelihood than extraversion and KAMF, i.e. while all are strong predictors when considering all stimuli together, either absorption/arousal, or extraversion/KAMF dominantly drive chills in specific sets of videos, indicating possible thematic clusters appealing to different axes of individual variation.

correlation for each stimulus (42), precluding the assumption of a random distribution of residual error in a conventional regression model. A mixed-effects logistic regression allowed us to model video ID as a random intercept, accounting for the dependence between observations from participants who saw the same stimuli. This helps satisfy the regression assumption of independent errors while still leveraging multiple responses per video in the analysis. Assumptions checked at this stage include the independence of observations between stimuli and a linear relationship between the log odds of the dependent variable and the predictor variables, such as age, gender, and ethnicity (Fig. 2). Categorical variables were presented as numbers (%) and compared using chi-square tests. Continuous variables were described as mean (standard deviation) and compared using the Student's t test (see Table 1 for technical details).

2. Assessing the role of psychological traits in chills experience: Building on the demographic baseline, we utilized multivariate logistic regression to incorporate psychological variables and assess their impact on the experience of aesthetic chills. The multilevel multivariate logistic regression models the probability of a binary outcome, i.e. chills' absence of presence, taking into account the simultaneous presence of multiple explanatory variables. The predictor variables in our model include sociodemographics and psychological traits. This modeling allows for the calculation of the effect of each variable on the probability of experiencing shivering, independently of the level of all other variables included in the model. We used validated scales like NEO-FFI for personality traits, MODTAS for absorption, and DPES and KAMF for affect disposition. Assumptions such as linearity, independence, and absence of multicollinearity were checked before the modeling.
3. Unveiling hidden sociocultural typologies through LCA: To discover underlying patterns affecting the experience of aesthetic chills, we implemented LCA. Prior, we attempted to reduce and understand the data association using principal component analysis. This analytical method allows us to identify what could be considered as "cultural DNA," or latent classes that cluster individuals based on unobserved heterogeneity. Assumptions for this analysis include the conditional independence of indicators within each latent class and a sufficiently large sample size for robust estimations. Variables such as age, gender, education, ethnicity, Latino, and political preferences were considered for sociocultural aspects, and appropriate scales were used for psychological aspects. The

optimal number of latent classes was determined based on statistical properties (AIC) when model convergence has been achieved (with a maximum number of iterations allowed of 10 millions).

Note that in order to account for multiple testing in those three first sections, we employed the Bonferroni correction method. Eighty-seven tests were executed for the main analysis (61 for both parts 1 and 2; 26 for part 3), and tests were considered significant for P-values < 0.0005. Furthermore, we included additional analyses using the standard 0.05 significance threshold in the Supplementary Material. These comprised 172 tests (145 for regression analysis and 27 for LCA). For these supplementary analyses, we did not apply the Bonferroni correction, as they served as sensitivity analyses to support the main findings. These analyses were primarily regression analyses where we varied the fitting models, rather than examining statistical associations between variables.

Step 2: predictive modeling of aesthetic chills: machine learning and cross-validation

1. Feature selection for machine learning analyses: Features included in the machine learning analysis described below were those pragmatically available to researchers before real-world assessments aiming to predict chills intensity. These features comprised age, education, sex, political preference, and prestimulus-exposure state, including arousal, valence, and mood. High-level summary metrics on trait variables such as DPES, KAMF, MODTAS, and NEO-FFI were also included. Data that would not be available before a video presentation, such as the specific video ID and whether the participant had previous exposure to that video, were not included in the feature set. Participants were excluded from the analysis if they had missing data or if any of the included features were not meaningfully acquired, such as a "prefer not to say" response to the biological sex question. The complete feature sets were generated by concatenating standardized responses of all included variables. Standardization was performed using z-score normalization, calculated across all participants within each feature.
2. Predicting the occurrence of chills: a SVM (c-SVC; radial basis function kernel; $c = 1$) was employed via libSVM in MATLAB. The feature set defined in the previous section and Table 5 was used for this classification task. A leave-25%-out-cross-validation approach was utilized here and repeated 10,000 times with final accuracies derived from averaging across each repetition. Importantly, before training the classifier, the number of exemplars per class (i.e. chills vs. no chills) was balanced by randomly sampling from the overrepresented class to match the number of exemplars in the underrepresented class. To evaluate the significance of the classification model, we constructed a cumulative distribution function with chance performance at 50% across 700 predictions. By plotting the actual number of correct classifications on the expected distribution, we derived a z-value and corresponding P-value, which jointly characterize our observations' location within the distribution and the probability of their chance occurrence. We repeated this effort a total of three times using the trait metrics at their highest summary level (15 features), subscale level (31 features), and individual questionnaire responses (141 features).
   To correct for multiple comparisons in this domain, even though the tests are not entirely independent, we conducted a stringent Bonferroni correction for three tests at $P < 0.05$ and, thus only considered P-values < 0.017. We then utilized Akaike's information criterion (AIC) and Bayesian information criterion (BIC) to compare all pairs of significant models to identify the most parsimonious model. Due to the complex nature of the coefficients and support vectors in SVM, we implemented a recursive feature elimination (RFE) technique to quantify the contribution of each feature within the most parsimonious, successful model. Specifically, we calculated the impact on classification accuracy when each feature was omitted from the feature set. Given that these were projected to be post hoc tests following a significant classification, we did not correct for multiple comparisons within this RFE approach. Finally, we conducted an exhaustive, exploratory feature-set combination analysis to identify which subset of features included in the original model would yield the most parsimonious model. We reported the top five models, based on classification performance in the Results section (Table 6). A fully exhaustive approach here constitutes 2,054 analyses, so we utilized a Bonferroni correct ($P < 2 \times 10^{-5}$) and only considered models that passed this threshold for subsequent AIC and BIC testing for parsimony.
3. Predicting chills intensity: Using custom MATLAB code (see Supplementary Material), we employed a LASSO regression model to predict chills intensity, a continuous variable ranging between 0 and 100. The model's regularization parameter (lambda; λ) was optimized using a leave-5%-out-cross-validation approach. Specifically, 5% of the dataset was randomly sampled to serve as the test set, while the remaining 95% constituted the training set for building the model. Using the intercept term and beta values from the training set, a weighted sum of features was computed for each participant in the test set to generate a predicted chills intensity ($\hat{Y}$). The root-mean-square-error (RMSE) was given by:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_i^n \left(Y_i - \widehat{Y}_i\right)^2}{n}}$$

This procedure was executed 10,000 times, with the RMSE averaged across each iteration. The process was replicated over a range of 100 lambda values spaced logarithmically between 0.0001 and 100. To mitigate overfitting, the lambda value (λ) yielding the lowest RMSE was then utilized in a leave-25%-out, 10,000-fold cross-validation, which generated the results reported herein. Mirroring the SVM efforts above, we also repeated these efforts with the three levels of trait summary metrics (individual responses, subscale, and highest summary level) and subjected resultant P-values to a Bonferroni corrected threshold ($P < 0.017$) to warrant subsequent AIC and BIC tests for parsimony. Beta coefficients allocated to each feature during each fold were averaged across the iterations and ordered by their absolute values to gauge their relative significance. The top five beta coefficients for the most parsimonious model are reported.

Ethics

The study was conducted in compliance with the Helsinki Declaration and was granted an exemption following review by Advarra IRB (Pro00068209). Participants provided informed consent and were informed about the purpose of the research, their right to decline or withdraw, and confidentiality limits.

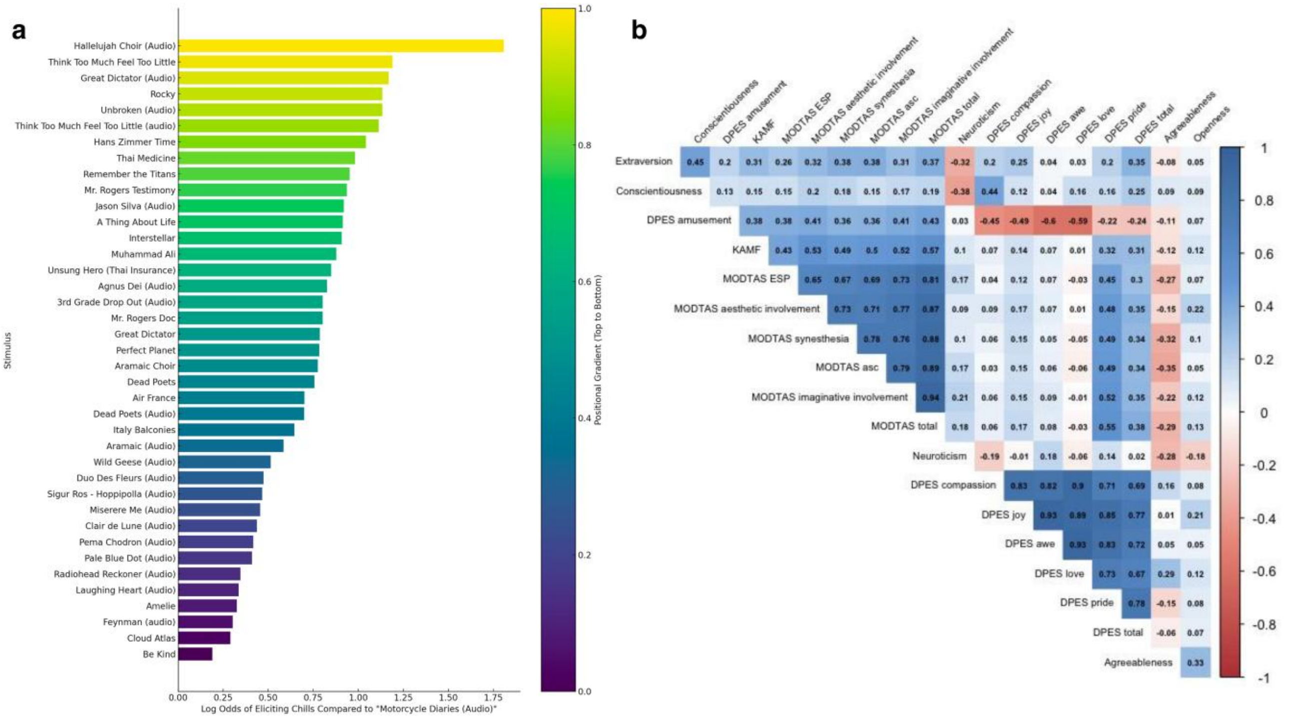

Fig. 3. Stimuli probability of eliciting chills a) and correlation heatmaps of psychological scales b). The bar chart illustrates the log odds of each stimulus eliciting chills when compared to "Motorcycle Diaries (Audio)" (the lowest chills ratio stimulus), which is used as the reference stimulus. The gradient color represents a visual ranking from top to bottom, with stimuli at the top having the highest probability of eliciting chills.

Participants were also given the opportunity to ask questions and receive answers about the phenomenon under study.

Results

Step 1: demographic, psychological, and sociocultural correlates

The likelihood of experiencing chills varied significantly depending on the stimulus presented

Using a classical logistic regression model, the stimulus "Hallelujah Choir (Audio)" had the highest odds ratio (OR) for inducing chills at 6.09 (95% CI: 3–12.84; $P < 0.01$; Fig. 3). Close contenders were "think too much feel too little" with an OR of 3.29 (95% CI: 1.68–6.57) and "Great Dictator (Audio)" with an OR of 3.22 (95% CI: 1.65–6.43), both also significant at $P < 0.01$. When comparing audio-only and audiovisual stimuli had an OR of 1.14 (95% CI: 0.99–1.32), which was not statistically significant ($P = 0.07$), indicating no significant difference in the likelihood of experiencing chills between audio and video stimuli.

State-related variables significantly influenced the likelihood of experiencing aesthetic chills

As described in the Materials and methods section, in order to account for the previous results and identify factors associated with chills independently of stimulus presentation, we employed a mixed-effects regression. Higher arousal levels showed increased odds of experiencing chills, with a univariate OR of 1.19 ($P < 0.01$). Similarly, higher valence levels were associated with an increased likelihood, displaying a univariate OR of 1.1 ($P < 0.01$). Elevated mood also significantly predicted chills, with a univariate OR of 1.49 ($P < 0.01$). Prior exposure to the stimulus drastically increased the odds, as shown by a univariate OR of 3.75 ($P < 0.01$) and a multivariate OR of 2.2 ($P < 0.01$). Overall, higher arousal, valence, and mood, as well as prior exposure to the stimulus, were strongly associated with a greater likelihood of experiencing aesthetic chills (Fig. 4).

Several demographic factors significantly increased the likelihood of experiencing aesthetic chills

Age groups 35–44 showed an increased OR of 2.1 in the univariate model ($P < 0.01$) and an OR of 1.36 in the multivariate model ($P = 0.07$). Individuals with a graduate or professional degree also had higher odds (univariate OR = 2.81, $P < 0.01$; multivariate OR = 1.15, $P = 0.42$; see Table 2). Males were more likely than females to experience chills (univariate OR = 1.85, $P < 0.01$; multivariate OR = 1.44, $P < 0.01$). Finally, participants who identified as Latino had increased odds in the univariate model (OR = 1.39, $P < 0.01$), although this was not significant in the multivariate model ($P = 0.06$). Overall, being in the age group of 35–44, having a higher educational level, and being male were identified as strong predictors for experiencing aesthetic chills.

In summary, being a middle-aged adult, having a graduate or professional degree, being male, identifying as Latino, and having democratic political preferences are independent factors that increase the likelihood of experiencing aesthetic chills, although not all of these remain significant in multivariate analysis (see Table 2).

Personality traits were significantly associated with the likelihood of experiencing aesthetic chills

Among the NEO-FFI personality traits, higher levels of extraversion were associated with increased odds of experiencing chills, with a univariate OR of 1.11 ($P < 0.01$) and a multivariate OR of 1.56 ($P < 0.01$). Similarly, higher levels of conscientiousness were linked to an increased likelihood, displaying a univariate OR of 1.07 ($P < 0.01$). Agreeableness showed a negative association

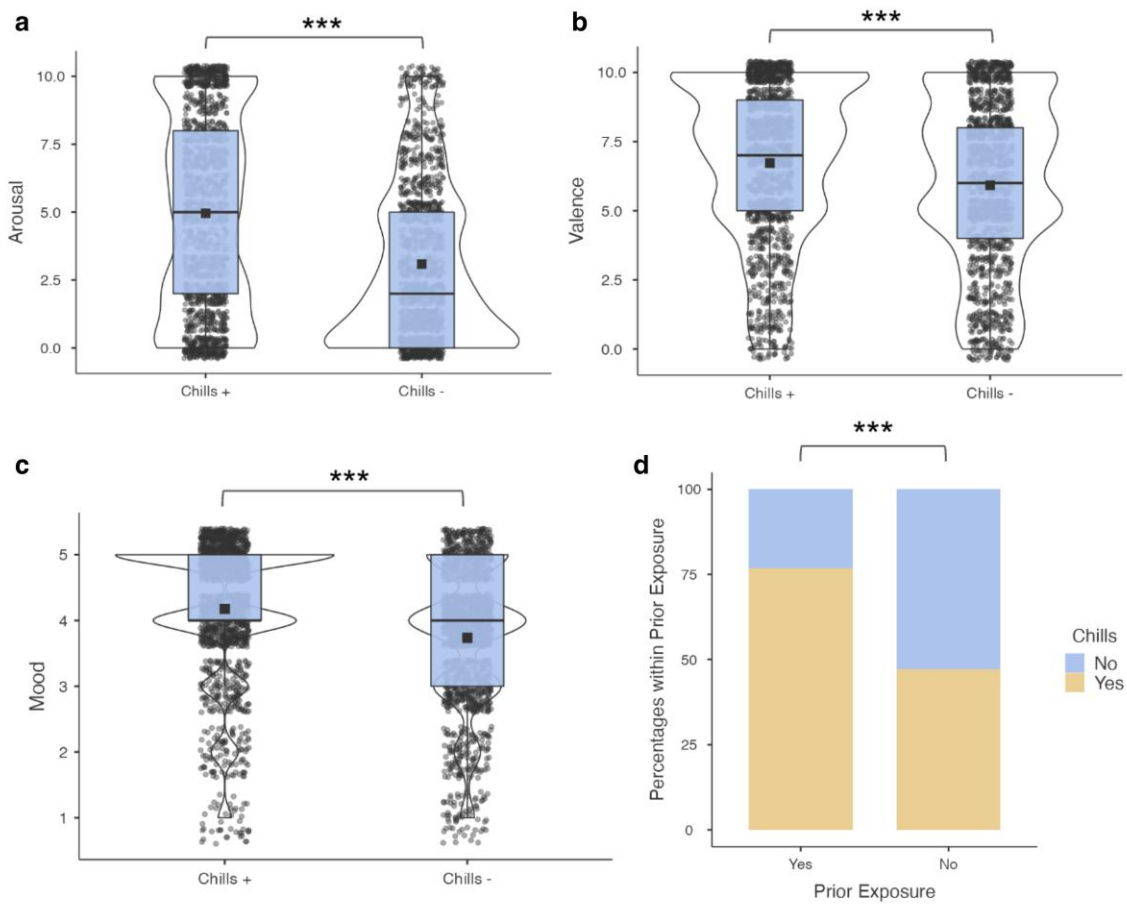

Fig. 4. Influence of state and prior exposure on aesthetic chills.

with a univariate OR of 0.93 ($P < 0.01$). Other psychological characteristics like synesthesia ($OR = 2.53$, $P < 0.01$), Asc ($OR = 2.62$, $P < 0.01$), aesthetic involvement ($OR = 2.49$, $P < 0.01$), imaginative involvement ($OR = 3$, $P < 0.01$), and DPES total score ($OR = 1.04$, $P < 0.01$) also significantly increased the likelihood of experiencing chills. In summary, higher levels of Extraversion, Conscientiousness, and certain psychological characteristics were strongly associated with a greater likelihood of experiencing aesthetic chills (Fig. 5).

In the demographic LCA, class D exhibited the highest prevalence of experiencing aesthetic chills at 88.2% (P < 0.01)

Demographically, this class was predominantly aged between 35 and 44 years. A significant 77.2% of individuals in this class held a graduate or professional degree, distinguishing them educationally ($P < 0.01$). In terms of personality traits, class D scored notably higher in extraversion (42.8), and conscientiousness (28.1), compared to the overall sample averages ($P < 0.01$). Moreover, this class led in specific psychological scales, most notably achieving the highest total MODTAS score of 128.6, significantly higher than the overall average ($P < 0.01$). These results are summarized in Table 3.

In the trait-based (psychological) LCA, class 7 had the highest frequency of individuals experiencing chills at 86.5% (P < 0.01)

This class consisted of 311 participants and scored the highest on the KAMF scale with a mean of 4.9 ($SD = 1.3$). On the MODTAS scale, class 7 also led in synesthesia (4.2), aesthetic involvement (4.2), and imaginative involvement (4.3). In terms of the DPES scores, this class had the highest mean scores in the categories of pride (31.3, $SD = 12.3$) and awe (49.0, $SD = 20.8$). Demographically, the age group of 35–44 made up 40.5% of this class. Individuals with a graduate or professional degree constituted 28.0% of the class, and 18.6% identified as Republican. When comparing sociodemographic and psychological traits across the seven groups, significant differences were observed in all these characteristics, each showing a P-value of less than 0.01 (see Table S10).

Step 2: machine learning and cross-validation

A combination of state, highest-level trait metrics, and demographics yield the most parsimonious predictive model of chills occurrence (SVM)

Using the feature set described above (highest-level summary trait metrics; 15 total features), the classification scheme yielded a highly significant prediction accuracy (68.2%; $P < 0.001$). Changing the feature set to include each trait's subscales (31 features), where available, did appear to quantitatively improve classification accuracy (70.5%; $P < 0.001$). Leveraging each trait's individual questionnaire responses (141 features) resulted in the highest classification accuracy (74%; $P < 0.001$). All three tests survived Bonferroni correction ($P < 0.017$). We employed AIC and BIC to compare two classification models, incorporating both accuracy and the number of features used. The criteria were calculated using the models' classification accuracy as a surrogate for likelihood, the number of observations, and the number of features. The original feature set was deemed to be preferred over the more extensive feature sets using both AIC and BIC comparisons.

Table 2. Comparative, univariate, bivariate, and multivariate analysis of sociodemographic characteristics, psychological scales, and state questionnaires according to chills status ($n = 2{,}937$).

	Descriptive analysis				Univariate mixed-effect logistic regression			Multivariate mixed-effect logistic regression	
	No ($n = 1{,}429$)	Yes ($n = 1{,}508$)	Total ($n = 2{,}937$)	P	OR (95% CI)	P	Mixed-effect variance	OR (95% CI)	P
Age				<0.01			0.069		
18–24	193 (13.5%)	204 (13.5%)	397 (13.5%)		Ref	—		Ref	—
25–34	184 (12.9%)	331 (21.9%)	515 (17.5%)		1.72 (1.31–2.25)	<0.01		1.28 (0.92–1.77)	0.14
35–44	192 (13.4%)	423 (28.1%)	615 (20.9%)		2.1 (1.62–2.74)	<0.01		1.36 (0.97–1.89)	0.07
45–54	181 (12.7%)	198 (13.1%)	379 (12.9%)		1.04 (0.78–1.38)	0.79		0.96 (0.67–1.37)	0.81
55–64	246 (17.2%)	132 (8.8%)	378 (12.9%)		0.5 (0.37–0.67)	<0.01		0.59 (0.41–0.85)	<0.01
65+	433 (30.3%)	220 (14.6%)	653 (22.2%)		0.47 (0.36–0.61)	<0.01		0.65 (0.47–0.91)	0.01
Education				<0.01			0.053		
High school diploma or GED	243 (17.0%)	216 (14.3%)	459 (15.6%)		Ref	—		Ref	—
Associates or technical degree	192 (13.4%)	165 (10.9%)	357 (12.2%)		0.97 (0.73–1.28)	0.81		0.86 (0.61–1.21)	0.38
Bachelor's degree	365 (25.5%)	368 (24.4%)	733 (25.0%)		1.14 (0.9–1.44)	0.29		0.64 (0.47–0.86)	<0.01
Graduate or professional degree	179 (12.5%)	443 (29.4%)	622 (21.2%)		2.81 (2.18–3.63)	<0.01		1.15 (0.82–1.61)	0.42
Some college, but no degree	398 (27.9%)	283 (18.8%)	681 (23.2%)		0.8 (0.63–1.02)	0.08		0.71 (0.53–0.95)	0.02
Some High school or less/Prefer not to say	52 (3.6%)	33 (2.2%)	85 (2.9%)		0.74 (0.46–1.2)	0.22		0.67 (0.38–1.19)	0.18
Gender				<0.01			0.057		
Female	872 (61.0%)	721 (47.8%)	1,593 (54.2%)		Ref	—			
Male	482 (33.7%)	735 (48.7%)	1,217 (41.4%)		1.85 (1.59–2.15)	<0.01		1.44 (1.18–1.76)	<0.01
Prefer not to say/other	75 (5.2%)	52 (3.4%)	127 (4.3%)		0.83 (0.57–1.2)	0.31		0.86 (0.55–1.34)	0.5
Ethnicity				0.06			0.057		
White or Caucasian	956 (66.9%)	1,093 (72.5%)	2,049 (69.8%)		Ref	—			
American Indian/Native American or Alaska Native	23 (1.6%)	21 (1.4%)	44 (1.5%)		0.8 (0.44–1.46)	0.47			
Asian	85 (5.9%)	61 (4.0%)	146 (5.0%)		0.62 (0.44–0.87)	0.01			
Black or African American	167 (11.7%)	179 (11.9%)	346 (11.8%)		0.93 (0.74–1.17)	0.56			
Mixed	39 (2.7%)	23 (1.5%)	62 (2.1%)		0.52 (0.3–0.88)	0.01			
Other	100 (7.0%)	95 (6.3%)	195 (6.6%)		0.84 (0.63–1.14)	0.26			
Prefer not to say	59 (4.1%)	36 (2.4%)	95 (3.2%)		0.53 (0.35–0.81)	<0.01			
Latino				0.04			0.06		
No	1,157 (83.6%)	1,167 (78.8%)	2,324 (81.1%)		Ref	—			
Yes	227 (16.4%)	314 (21.2%)	541 (18.9%)		1.39 (1.15–1.68)	<0.01			
Political preferences				<0.01			0.05		
Democrat	600 (42.0%)	863 (57.3%)	1,463 (49.8%)		Ref	—		Ref	—
Independent	363 (25.4%)	260 (17.3%)	623 (21.2%)		0.5 (0.42–0.61)	<0.01		0.64 (0.51–0.81)	<0.01
No preference	128 (9.0%)	73 (4.8%)	201 (6.8%)		0.4 (0.29–0.54)	<0.01		0.57 (0.39–0.83)	<0.01
Other	35 (2.5%)	14 (0.9%)	49 (1.7%)		0.28 (0.15–0.52)	<0.01		0.36 (0.17–0.75)	0.01
Republican	302 (21.1%)	297 (19.7%)	599 (20.4%)		0.68 (0.56–0.83)	<0.01		0.92 (0.73–1.17)	0.52
Personnality traits (NEO-FFI)									
Neuroticism	35.8 (9.5)	36.2 (8.2)	36.0 (8.9)	1	1.01 (1–1.02)	0.11	0.058		
Agreeableness	41.1 (4.9)	38.6 (6.4)	39.8 (5.9)	<0.01	0.93 (0.91–0.94)	<0.01	0.058	0.92 (0.82–1.03)	0.13
Extraversion	35.3 (7.1)	40.4 (6.9)	37.9 (7.4)	<0.01	1.11 (1.1–1.13)	<0.01	0.07	1.56 (1.41–1.73)	<0.01
Conscientiousness	25.8 (4.5)	27.1 (4.3)	26.5 (4.5)	<0.01	1.07 (1.05–1.09)	<0.01	0.057		
Openness	31.0 (4.1)	31.1 (4.0)	31.0 (4.0)	1	1.01 (0.99–1.03)	0.42	0.057		
MODTAS									
Synesthesia	2.4 (1.0)	3.5 (1.0)	3.0 (1.1)	<0.01	2.53 (2.33–2.75)	<0.01	0.081		
Asc	2.4 (1.0)	3.4 (1.0)	3.0 (1.1)	<0.01	2.62 (2.41–2.85)	<0.01	0.093		
Aesthetic involvement	3.0 (1.0)	3.7 (0.8)	3.3 (1.0)	<0.01	2.49 (2.27–2.73)	<0.01	0.077		
Imaginative involvement	3.0 (0.9)	3.7 (0.7)	3.3 (0.9)	<0.01	3 (2.7–3.33)	<0.01	0.081		
ESP					1.93 (1.79–2.09)	<0.01	0.059		

(continued)

Table 2. Continued

	Descriptive analysis				Univariate mixed-effect logistic regression			Multivariate mixed-effect logistic regression	
	No (n = 1,429)	Yes (n = 1,508)	Total (n = 2,937)	P	OR (95% CI)	P	Mixed-effect variance	OR (95% CI)	P
Total score	94.0 (28.1)	122.1 (25.1)	108.4 (30.1)	<0.01	1.04 (1.04–1.04)	<0.01	0.09	1.52 (1.22–1.9)	<0.01
KAMF	3.3 (1.3)	4.5 (1.3)	3.9 (1.4)	<0.01	2.03 (1.9–2.17)	<0.01	0.118	1.91 (1.7–2.16)	<0.01
DPES	2.8 (1.1)	3.5 (1.0)	3.1 (1.1)	<0.01					
Compassion	10.3 (2.6)	10.4 (2.7)	10.3 (2.6)	1	1.04 (1–1.07)	0.05	0.064		
Awe	49.8 (19.9)	50.3 (20.4)	50.1 (20.2)	1	1 (1–1.01)	0.23	0.063	0.52 (0.36–0.75)	<0.01
Joy	16.0 (5.2)	17.0 (5.7)	16.5 (5.5)	<0.01	1.22 (1.17–1.27)	<0.01	1.108		
Love	18.3 (6.2)	17.7 (6.2)	18.0 (6.2)	0.29	0.97 (0.95–0.99)	<0.01	0.078		
Pride	22.3 (9.3)	27.6 (11.3)	25.1 (10.7)	<0.01	1.17 (1.15–1.19)	<0.01	2.022	1.84 (1.25–2.72)	<0.01
Amusement	2.8 (1.3)	3.4 (1.1)	3.1 (1.2)	<0.01	1.85 (1.69–2.03)	<0.01	0.264	0.8 (0.69–0.94)	0.01
Total score	278.9 (55.2)	306.5 (59.1)	293.1 (58.9)	<0.01	1.02 (1.01–1.02)	<0.01	0.556		
State									
Arousal	3.1 (3.0)	5.0 (3.5)	4.0 (3.4)	<0.01	1.19 (1.16–1.22)	<0.01	0.063		
Valence	5.9 (3.0)	6.7 (2.9)	6.3 (3.0)	<0.01	1.1 (1.07–1.12)	<0.01	0.057		
Mood	3.7 (1.1)	4.2 (1.0)	4.0 (1.1)	<0.01	1.49 (1.38–1.6)	<0.01	0.054		
Prior exposure	95 (6.6%)	315 (20.9%)	410 (14.0%)	<0.01	3.75 (2.93–4.8)	<0.01	0.051	2.2 (1.62–2.99)	<0.01

Data are presented as mean (SD) for quantitative values and n (%) for categorical data. Univariate analysis includes each variable and stimulus as a mixed-effect variable. Multivariable analysis included all the presented variables and stimuli as a mixed effect. For this model, the stimulus intercept variance is 0.11 (number of observations: 2,935, stimulus groups: 40). ESP, extrasensory perception; GED, general educational development.

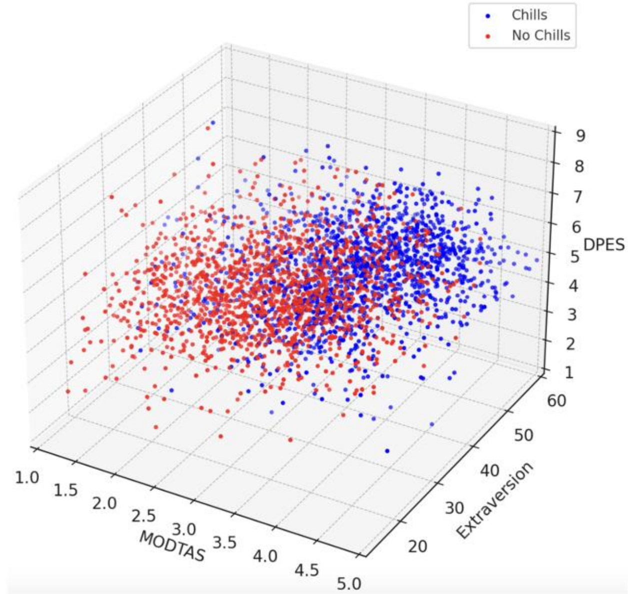

Fig. 5. Contribution of personality to chills. The plot illustrates a cube constructed in a three-dimensional space with dimensions corresponding to MODTAS, extraversion, and DPES values, where data points colored in blue (representing "yes") and red (representing "no") indicate the presence of two distinct clusters.

Accordingly, subsequent investigations into the importance of features utilized classification results with the original feature set composed of the highest-level summary trait metrics. The RFE revealed that no single feature significantly impacted the accuracy of the model according to the AIC and BIC (Table 4), indicating a robust, multivariate dependency within the model.

The exhaustive, exploratory feature-set combination analysis resulted in a total of 2,054 analyses, representing the number of unique combinations across all demographic, trait, and state measures available. The highest classification accuracy observed was 73.5% ($P < 0.001$) when age, sex, arousal, KAMF, and MODTAS were included in the feature set. Both AIC and BIC comparisons revealed that the model with these five features yielded significantly higher classification values than the model above that used all the highest-level trait metrics (15 total features). The five highest classification accuracy from this feature-set search are reported alongside the features included are displayed in Table 5. All reported values passed the Bonferroni threshold identified for this exhaustive analysis ($P < 2 \times 10^{-5}$). Upon a preliminary review, it's evident that while the feature sets have distinct compositions and yield comparable classification accuracies, only KAMF, MODTAS, and Sex consistently appear across the highest-performing sets, suggesting their potential cruciality for successful classification.

A combination of state, trait, and demographics predict chills intensity (LASSO)

In line with the predefined exclusion criteria, each fold of the leave-25%-out-cross-validation comprised 2,097 participants in the training set and 700 participants in the test set. The lambda value (λ) that minimized the RMSE was 0.248. Utilizing the feature set defined above accounted for a significant portion of the variance ($R = 0.482$; $R^2 = 0.232$, $P < 0.00001$) with a meaningfully low RMSE of 22.01, suggesting that, on-average, the prediction was off by ~22% in predicting an individual's chills intensity.

Table 3. LCA insights: demographics, personality, and emotions.

	Class A (*n* = 114)	Class B (*n* = 1,447)	Class C (*n* = 377)	Class D (*n* = 451)	Class E (n = 548)	Total (*n* = 2,937)	P
Chills							<0.01
No	62 (54.4%)	867 (59.9%)	180 (47.7%)	53 (11.8%)	267 (48.7%)	1,429 (48.7%)	
Yes	52 (45.6%)	580 (40.1%)	197 (52.3%)	398 (88.2%)	281 (51.3%)	1,508 (51.3%)	
Age							<0.01
18–24	24 (21.1%)	0 (0.0%)	138 (36.6%)	0 (0.0%)	235 (42.9%)	397 (13.5%)	
25–34	26 (22.8%)	113 (7.8%)	103 (27.3%)	107 (23.7%)	166 (30.3%)	515 (17.5%)	
35–44	22 (19.3%)	175 (12.1%)	81 (21.5%)	263 (58.3%)	74 (13.5%)	615 (20.9%)	
45–54	19 (16.7%)	223 (15.4%)	31 (8.2%)	55 (12.2%)	51 (9.3%)	379 (12.9%)	
55–64	17 (14.9%)	327 (22.6%)	12 (3.2%)	0 (0.0%)	22 (4.0%)	378 (12.9%)	
65+	6 (5.3%)	609 (42.1%)	12 (3.2%)	26 (5.8%)	0 (0.0%)	653 (22.2%)	
Education							<0.01
High school diploma or GED	29 (25.4%)	148 (10.2%)	120 (31.8%)	0 (0.0%)	162 (29.6%)	459 (15.6%)	
Associate or technical degree	15 (13.2%)	238 (16.4%)	51 (13.5%)	0 (0.0%)	53 (9.7%)	357 (12.2%)	
Bachelor's degree	13 (11.4%)	446 (30.8%)	57 (15.1%)	101 (22.4%)	116 (21.2%)	733 (25.0%)	
Graduate or professional degree (MA, MS, MBA, PhD, JD, MD, DDS, etc.)	3 (2.6%)	210 (14.5%)	9 (2.4%)	348 (77.2%)	52 (9.5%)	622 (21.2%)	
Prefer not to say	2 (1.8%)	1 (0.1%)	6 (1.6%)	0 (0.0%)	4 (0.7%)	13 (0.4%)	
Some college, but no degree	43 (37.7%)	391 (27.0%)	105 (27.9%)	0 (0.0%)	142 (25.9%)	681 (23.2%)	
Some High school or less	9 (7.9%)	13 (0.9%)	29 (7.7%)	2 (0.4%)	19 (3.5%)	72 (2.5%)	
Gender							<0.01
Female	8 (7.0%)	914 (63.2%)	260 (69.0%)	47 (10.4%)	364 (66.4%)	1,593 (54.2%)	
Male	0 (0.0%)	516 (35.7%)	114 (30.2%)	403 (89.4%)	184 (33.6%)	1,217 (41.4%)	
Prefer not to say/other	106 (93.0%)	17 (1.2%)	3 (0.8%)	1 (0.2%)	0 (0.0%)	127 (4.3%)	
Ethnicity							<0.01
White or Caucasian	28 (24.6%)	1,250 (86.4%)	147 (39.0%)	440 (97.6%)	184 (33.6%)	2,049 (69.8%)	
American Indian/Native American or Alaska Native	1 (0.9%)	11 (0.8%)	32 (8.5%)	0 (0.0%)	0 (0.0%)	44 (1.5%)	
Asian	2 (1.8%)	71 (4.9%)	0 (0.0%)	7 (1.6%)	66 (12.0%)	146 (5.0%)	
Black or African American	12 (10.5%)	91 (6.3%)	0 (0.0%)	0 (0.0%)	243 (44.3%)	346 (11.8%)	
Mixed	3 (2.6%)	5 (0.3%)	1 (0.3%)	4 (0.9%)	49 (8.9%)	62 (2.1%)	
Native Hawaiian or other Pacific Islander	1 (0.9%)	2 (0.1%)	0 (0.0%)	0 (0.0%)	6 (1.1%)	9 (0.3%)	
Other	0 (0.0%)	8 (0.6%)	178 (47.2%)	0 (0.0%)	0 (0.0%)	186 (6.3%)	
Prefer not to say	67 (58.8%)	9 (0.6%)	19 (5.0%)	0 (0.0%)	0 (0.0%)	95 (3.2%)	
Latino							<0.01
No	55 (79.7%)	1,399 (97.8%)	20 (5.3%)	409 (91.1%)	441 (81.4%)	2,324 (81.1%)	
Yes	14 (20.3%)	31 (2.2%)	355 (94.7%)	40 (8.9%)	101 (18.6%)	541 (18.9%)	
Political preferences							<0.01
Democrat	39 (34.5%)	630 (43.5%)	129 (34.2%)	421 (93.3%)	244 (44.6%)	1,463 (49.8%)	
Independent	33 (29.2%)	344 (23.8%)	133 (35.3%)	8 (1.8%)	105 (19.2%)	623 (21.2%)	
No preference	21 (18.6%)	26 (1.8%)	53 (14.1%)	0 (0.0%)	101 (18.5%)	201 (6.8%)	
Other	0 (0.0%)	34 (2.3%)	11 (2.9%)	0 (0.0%)	4 (0.7%)	49 (1.7%)	
Republican	20 (17.7%)	413 (28.5%)	51 (13.5%)	22 (4.9%)	93 (17.0%)	599 (20.4%)	
Personnality traits (NEO-FFI)							
Neuroticism	38.2 (8.5)	33.9 (9.3)	39.1 (7.6)	36.0 (7.4)	39.0 (8.0)	36.0 (8.9)	<0.01
Agreeableness	39.8 (6.0)	41.7 (5.0)	39.6 (5.8)	35.3 (6.1)	38.9 (5.7)	39.8 (5.9)	<0.01
Extraversion	37.3 (6.9)	37.0 (7.5)	36.6 (6.6)	42.8 (6.4)	37.3 (7.1)	37.9 (7.4)	<0.01
Conscientiousness	24.7 (4.5)	26.9 (4.2)	25.0 (4.6)	28.1 (4.0)	25.4 (4.6)	26.5 (4.5)	<0.01
Openness	30.6 (3.6)	31.7 (4.1)	30.9 (3.9)	29.9 (3.7)	30.6 (3.9)	31.0 (4.0)	<0.01
MODTAS							
Synesthesia	3.0 (1.1)	2.7 (1.1)	3.0 (1.1)	3.8 (0.9)	3.0 (1.1)	3.0 (1.1)	<0.01
Asc	3.0 (1.1)	2.6 (1.1)	3.1 (1.1)	3.8 (0.9)	3.1 (1.1)	3.0 (1.1)	<0.01
Aesthetic involvement	3.3 (1.0)	3.2 (1.0)	3.4 (1.0)	3.8 (0.8)	3.3 (1.0)	3.3 (1.0)	<0.01
Imaginative involvement	3.3 (0.9)	3.1 (0.9)	3.5 (0.8)	3.8 (0.7)	3.4 (0.9)	3.3 (0.9)	<0.01
ESP	3.2 (1.1)	2.9 (1.1)	3.2 (1.1)	3.7 (0.9)	3.2 (1.0)	3.1 (1.1)	<0.01
Total score	107.5 (29.7)	100.4 (29.9)	111.9 (27.1)	128.6 (24.0)	110.7 (28.5)	108.4 (30.1)	<0.01
DPES							
Compassion	10.2 (2.1)	10.4 (2.9)	10.0 (2.3)	10.7 (2.6)	10.2 (2.3)	10.3 (2.6)	<0.01
Awe	52.7 (17.9)	48.1 (21.6)	52.4 (18.3)	50.9 (19.3)	52.5 (18.2)	50.1 (20.2)	<0.01
Joy	17.0 (4.6)	16.0 (5.8)	16.8 (4.9)	17.6 (5.6)	16.9 (4.9)	16.5 (5.5)	<0.01
Love	18.3 (5.3)	18.1 (6.8)	18.1 (5.6)	17.1 (5.7)	18.1 (5.5)	18.0 (6.2)	0.05
Pride	25.9 (9.7)	22.8 (10.5)	26.3 (9.9)	29.7 (11.3)	26.2 (9.8)	25.1 (10.7)	<0.01
Amusement	3.0 (1.0)	3.1 (1.4)	3.0 (1.1)	3.5 (1.1)	3.0 (1.1)	3.1 (1.2)	<0.01
Total score	292.7 (56.6)	284.0 (58.8)	290.9 (55.0)	322.8 (57.4)	294.3 (55.3)	293.1 (58.9)	<0.01
KAMF	3.9 (1.4)	3.7 (1.4)	3.9 (1.4)	4.7 (1.4)	3.8 (1.5)	3.9 (1.4)	<0.01

Five classes were identified with LCA over demographics. Four thousand three hundred and forty-nine iterations were needed to achieve convergence. For traits: 1,688 iterations before convergence. ESP, extrasensory perception; GED, general educational development.

Mirroring the SVM efforts and retraining the model with trait subscales, where available, did not improve the model's predictive power (R = 0.4579; RMSE = 22.354). Neither did employ individual questionnaire responses (R = 0.4293; RMSE = 23.1480). All these models produced *P*-values that passed Bonferroni correction, but the original model (with summary-level metrics) was the

Table 4. Impacts to classification accuracy as a function of recursively eliminating each feature from the feature set.

Excluded feature	Classification accuracy % when removed
Age	67.7%
Education	67.5%
Sex	68.3%
Political preference	67.7%
Prestimulus-exposure arousal	67.8%
Prestimulus-exposure valence	68.5%
Prestimulus-exposure mood	67.7%
DPES	72.1%
KAMF	67.4%
MODTAS	67.2%
NEO-FFI	67.7%

Table 5. Top 5 classification accuracies resulting from an exhaustive feature-set combination analysis.

(Num features) feature set	Classification accuracy %
Reference/original: (15) age, education, sex, political preference, prestimulus-exposure states (arousal, valence, mood), DPES, KAMF, MODTAS, NEO-FFI (incl. extraversion, neuroticism, conscientiousness, openness, agreeableness)	68.2%
(5) Age, sex, arousal, KAMF, MODTAS	73.5%[a]
(6) Age, sex, political preference, arousal, KAMF, MODTAS	73.4%
(6) Age, sex, arousal, mood, KAMF, MODTAS	73.4%
(7) Education, SEX, POLITICAL PREFERENCE, AROUSAL, DPES, KAMF, MODTAS	73.3%
(6) Age, education, sex, valence, KAMF, MODTAS	73.2%

[a]Indicates statistically significant differences (AIC and BIC) in classification accuracy and parsimony. All accuracies reported below pass a Bonferroni corrected P-threshold ($P < 2 \times 10^{-5}$) on the 2,054 feature sets explored.

Table 6. Ranking of means and standard deviations of beta coefficients across 40 per-stimulus logistic regression analyses of traits and demographics against chills likelihood.

Covariate	Average	SD
MODTAS	2.97921623	2.37861784
KAMF	2.86222329	1.9008434
Age	2.06161718	2.6238751
Mood pre	1.84022947	2.10340461
Arousal pre	1.71085481	1.74232628
Extraversion	1.48360721	1.64966522
Neuroticism	1.45398152	1.60816908
Conscientiousness	1.39484965	1.90643316
Openness	1.27359465	1.42822668
valence pre	1.23248549	1.3887474
Sex	1.1583133	1.39520332
Political orientation	1.15220677	1.59848186
Agreeableness	1.06747129	1.16897125
DPES	1.06187925	1.28178454
Education	0.94246302	0.81025342

most parsimonious. The highest-ranking features from the utilized feature set (age, sex, education, political preference, arousal, valence, mood, DPES, KAMF, MODTAS, and NEO-FFI) in the LASSO model by absolute beta values were MODTAS ($\beta = 6.2878$), sex ($\beta = 3.205$), KAMF ($\beta = 2.635$), political preference ($\beta = -1.081$), and prestimulus-exposure mood ($\beta = 1.08$).

Discussion

This study utilized a multilevel statistical method to provide a comprehensive understanding of the factors contributing to the experience of aesthetic chills. Among the stimuli tested, the "Hallelujah Choir (Audio)" was notably effective in eliciting chills. Moreover, age, educational level, and gender were identified as strong predictors of experiencing this phenomenon. Crucially, arousal at baseline seems to be a key predictor confirming the findings of Mori and Iwanaga (39). The results were consistent whether applying the classical or mixed method, even when introducing a fixed effect on prior exposure. The LCA revealed hidden classes of individuals who are significantly more likely to experience aesthetic chills.

Certain latent classes—specifically, class D in the demographic LCA and class 7 in the psychological LCA—exhibited a notably high prevalence of experiencing aesthetic chills. Class D, which consisted predominantly of individuals aged between 35 and 44 years and with a higher educational level, had an 88.2% rate of experiencing aesthetic chills. This class also scored significantly higher in personality traits such as extraversion and conscientiousness and led in the MODTAS psychological scale. Similarly, class 7, which consisted of 311 participants, led to experiencing chills at a rate of 86.5%. This class also scored highest in multiple psychological scales, including KAMF, and in the MODTAS subscales of synesthesia, aesthetic involvement, and imaginative involvement. Interestingly, the age group of 35–44 also constituted a significant portion of class 7. These observations may point to a specific profile of individuals who are more predisposed to experiencing aesthetic chills, suggesting the role of certain demographic and psychological factors in this unique emotional experience. The high prevalence of aesthetic chills in these hidden classes raises important questions for future research, especially in understanding the underlying mechanisms that contribute to such heightened emotional experiences. These findings could also be instrumental in clustering patients who are most likely to benefit from chills-based interventions and providing each patient with personalized exposure.

Interestingly, class D and class 7 not only exhibited a high prevalence of aesthetic chills but also scored significantly higher on psychological scales related to emotional and aesthetic involvement, such as MODTAS and KAMF. It is plausible that individuals in these classes have a unique way of processing emotional and sensory information, making them more receptive to the aspects of stimuli that elicit chills (24, 30, 31, 34, 35, 37, 38).

Preliminary evidence suggests that musical chills are mediated by interoceptive awareness (53–55), and subjects experiencing musical chills display improved emotional awareness compared to those who did not, speaking to the role of interoceptive inference in the chills process (7, 55). To further elucidate this phenomenon, future research could explore the neural mechanisms underlying these differences in emotional processing. Investigating whether these individuals have distinct neural pathways or activations in response to aesthetic stimuli could offer valuable insights into why they experience chills more frequently and intensely. Sachs et al. (32) found that individual differences in chills and musical reward sensitivity are tied to white matter connectivity between sensory processing areas in the superior temporal gyrus and emotional and social processing areas in the insula and medial prefrontal cortex. Another study by Williams et al. (34, 35, 38) found that participants reporting greater proneness to aesthetic chills responses exhibited significantly higher connectivity between the default network and sensory and motor cortices, higher connectivity between the ventral default and salience networks, and decreased connectivity between the cerebellum and somatomotor cortex. The susceptibility to aesthetic chills in these latent classes could be indicative of underlying neural mechanisms that facilitate greater sensory access to emotional and social reward systems (22, 24).

Building on McCrae's (30) suggestion that aesthetic chills may serve as a universal marker of "openness to experience," our LCA instead revealed different personality traits of extraversion and conscientiousness. These traits, along with elevated scores on psychological scales like MODTAS and KAMF, could serve as more nuanced indicators of "openness." Indeed, the finding that MODTAS and KAMF were the two trait metrics contained in the feature set that yielded the highest predictive accuracy for the occurrence of chills suggests that, in this context, these measures are more sensitive than the NEO-FFI. Silvia and Nusbaum (31) also found that openness to experience and expertise in the arts are significant contributors to experiencing aesthetic chills. Given that both aesthetic chills and Extraversion are mediated by dopaminergic reward pathways (9, 12, 24, 25), it stands to reason that class D's heightened propensity for chills is underpinned by these dopaminergic mechanisms (56).

The latent classes can be likened to distinctive microcultures within the larger population of Southern California. Remarkably, the classes that exhibit heightened chills sensitivity are characterized by specific demographic and psychological traits that are commonly observed in this region. The concept of "cultural resonance" might explain how the demographic and psychological attributes of individuals in these latent classes align with their surrounding culture (57–59). This would explain why these individuals may tend to manifest greater extroversion and heightened tendencies for immersion in daily experiences. Cultural resonance also potentially facilitates the emergence of positive emotions and strong reactions to cultural artifacts, as their individual attributes and values correspond with the prevalent cultural norms of their social context (60–64).

While the application of LCA provided robust insights into the subpopulations more predisposed to aesthetic chills, the study's limitations warrant cautious interpretation. First, there could be diluted effects from averaging together heterogeneous forms of chills. Indeed, the use of a mixed-effects model typically tends to attenuate the estimates of each regression coefficient since these models are more restrictive compared to conventional models, and this strengthens our confidence in the independent association of each parameter with chills. However, the geographical confinement to Southern California and the cross-sectional nature of the data collection constrain the extrapolation of these findings to broader demographics and over time scales. Given these caveats, future research should aim for more geographically diverse and longitudinal designs to validate and extend our observations.

Considering gender differences in personality across the ten aspects of the big five and that much larger effect sizes have been observed at the level of the aspects for both gender and political orientation differences, future work should investigate these trends further (65). It is noteworthy that multivariate methods, as opposed to univariate methods, are known to unveil larger effects when applied to gender analyses, and our findings align with this broader trend (66). Recognizing this, we incorporated this consideration into our study, employing a comprehensive statistical methodology to account for this effect.

Considering the strong genetic basis of the absorption trait (67) and Bignardi et al.'s finding (40) that 36% of the variance in feeling aesthetic chills can be explained by additive genetic factors and the remaining 64% by environmental sources of variation, the incorporation of genetic and neuroimaging methodologies could enrich our understanding of these complex emotional phenomena. Thus, while LCA serves as a powerful tool for dissecting heterogeneity in aesthetic experiences, these findings should invite more comprehensive studies including physiological measures, especially given the diluted effects from averaging together heterogenous forms of chills.

Conclusion

This study sheds light on the age-old question of why the same experience can evoke profoundly different reactions in different individuals. The obtained results mark a significant step forward in the development of personalized stimuli for experiments in neuroimaging and affective neuroscience. Our findings suggest that the experience of aesthetic chills is far from random; it is shaped by a complex interplay of predictable individual and cultural factors. Variable collected before stimulus exposure such as age, sex, arousal, KAMF, and MODTAS consistently prognosticated chills occurrence, irrespective of the specific stimulus presented. This suggests that knowing these factors beforehand can help predict if a stimulus, known for inducing chills, will actually have that effect on participants, thereby increasing experimental control and decreasing unexplained variability. Future research could focus on creating tailored models for individual stimuli and participant populations, aiming to best match participants with stimuli most likely to elicit chills in each individual participant. Further, the notion of "cultural resonance" to account for the chills latent class identified provides some answers to the question posed at the beginning of this article. Yes, beauty may be in the eye of the beholder, but it is also deeply embedded in the cultural and psychological fabric of the beholder. As we move forward in this line of research, the insights gained hold promise not only for understanding the complexities of human emotion but also for the clinical applications of these powerful emotional experiences.

Supplementary Material

Supplementary material is available at *PNAS Nexus* online.

Funding

This work was funded by Tiny Blue Dot Foundation and the Mordechai Walder Charitable Fund.

Author Contributions

Conceptualization: F.S., L.C.-M., N.R., C.L.; methodology: F.S., L.C.-M., N.R., C.L.; investigation: F.S., L.C.-M., N.R., C.L.; visualization: F.S.; analysis: T.D., F.S., L.C.-M., N.R.; writing: all.

Data Availability

All data are available in the main text or the supplementary material. The ChillsDB 2.0 dataset is released under a Creative Commons Attribution 4.0 International (CC BY 4.0) license on FigShare. This allows others to freely share and adapt the dataset as long as appropriate credit is given to the original creators by citing the published paper (7). The dataset is divided into two .csv files available under a CC BY 4.0 license on the associated FigShare (ChillsDB2). For a comprehensive understanding of each column, researchers are advised to refer to the Header Explanation File. All code supporting these analytical efforts is included in the following repository. Note: Requires the LibSVM toolbox. https://github.com/Institute-for-Advanced-Consciousness/E4-F01.

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