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Groovin' to the Cultural Beat: Preferences for Danceable Music Represent Cultural Affordances for High-Arousal Negative Emotions

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Music is a product of culture. Cross-cultural examinations of music features can reveal novel information about the cultural psychological processes involved in shaping music preferences. In Studies 1 and 2, we first identified differences in music preferences through machine learning of East-Asian and Western popular music on Spotify (combined $N = 1{,}006{,}644$). In interpreting these results, we developed a theory on danceability as a music feature, that represents cultural affordances for high-arousal emotions. Subsequent confirmatory studies (Studies 3–5, combined $N_{\text{songs}} = 3{,}343$, $N_{\text{participants}} = 495$, $N_{\text{countries}} = 60$) tested this theory by examining danceability and the role of emotion in music preferences. Specifically, we found that danceability represents cultural affordances for high-arousal negative (HAN) emotions: societies with greater HAN emotion prevalence generally prefer listening to more danceable music. Consistently, this was also observed more in independent individuals and culturally looser countries. Using evidence from Japanese and American participants (Study 5), we propose a mechanism through discharge regulation in music: cultures with looser cultural norms would also have more experiences of HAN emotions in daily life. Discharge regulation, which is listening to music to cathartically release HAN emotions, would then skew music preferences toward high-arousal (danceable) music to facilitate this cathartic HAN downregulation. These findings have implications for cross-cultural research by demonstrating that music features, being widely accessible and almost universally perceived, can quantify cultural tendencies toward affective (HAN emotion) norms beyond commonly used self-report paradigms.

Keywords: cross-culture, music preference, emotion regulation, danceability, machine learning

Music is powerful, emotive, and prevalent across cultures and history (Dunbar, 2012). Despite some cross-cultural variations in the experience of music, there is considerable agreement that statistical universals exist in the way music is *perceived* (Cowen et al., 2020; Fritz et al., 2009; Purves, 2017; Stevens & Byron, 2016). Thus, cross-cultural variation may often imply differences in music *preference*: functions and inclinations that afford preference for specific types of music over others (Cross, 2001; Juslin et al., 2016). In this article, we explore cultural differences in music preferences as a reflection of wider sociocultural trends. Specifically, we posit that cultural differences in preferred musical features can be explained by the psychological affordances for those features, and the value of those affordances varies by culture.

Music as a Cultural Product

Preferences for different products—defined here as objects or constructs with a physical basis—vary across cultures. This is evident in consumption behavior, such as choosing music consistent with culturally determined affect values (Tsai et al., 2007) and choosing products based on societal values of uniqueness versus conformity seeking (Kim & Markus, 1999). This is also evident in production, where products are created to fit shared values and esthetics (e.g., analytic vs.

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All online supplementary material is located in our OSF (Open Science Framework) repository: https://osf.io/hg7sc/?view_only=9bb77cab0c7642af98c4fc37980627ac. This includes code for data collection and analysis from the R programming environment, as well as raw Jamovi output for analyses in Jamovi. Where applicable, data are available online. Data are also available upon request to the corresponding author.
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holistic attention styles, Wang et al., 2012). These "cultural" products are public, tangible, and shared, reflecting the intersubjective consensus of a given culture (Lamoreaux & Morling, 2012; Morling & Lamoreaux, 2008). Cultural products are commonly used in research to quantify real-world cultural differences beyond self-report questionnaires to support and reinforce current theory (e.g., individualism–collectivism: Morling & Lamoreaux, 2008; analysis–holism: Masuda et al., 2008). Such research allows for examinations of culture beyond the laboratory setting, with real-world consequences in consumption and behavior. The cultural values of a society may thus afford preferences for certain styles or characteristics of music. Music, in particular, may hold several benefits over other frequently used products (e.g., news articles, tweets, and children's books) due to the widespread availability of related data and universality in perception, that provides usable data for cross-cultural (products) research.

Firstly, due to the recent growth of the field of music information retrieval, and the prevalence of music streaming technology, huge databases have become available to researchers (e.g., Bertin-Mahieux et al., 2011; Meseguer-Brocal et al., 2017). New music is constantly being released and ranked, capturing contemporary and historical trends across cultures. Knowing how cultural values are mapped on to music may thus allow for convenient, online tracking of cultural change and comparisons through these massive cultural (music) product databases. Moreover, these databases contain information about the structural make-up of songs, through music features such as rhythm and tempo. Some low-level features can also be combined to form more complex features, such as danceability (rhythmic salience) or dissonance, that quantify music. Secondly, these musical features reliably reflect individuals' perceptions of music (see Fricke et al., 2018), and are strongly consistent with music-emotion recognition across cultures (Balkwill & Thompson, 1999; Balkwill et al., 2004). For example, music with strong rhythmic and percussive features is almost universally perceived as highly arousing (Mehr et al., 2019), and is strongly associated with dance across cultures (Savage et al., 2015). Yet, much less is known about cultural differences in music preferences and their implications on everyday emotional experiences, which is an area we explore with the present research.

The cross-cultural consistency between features and perception enables us to assume that significant cultural variation in musical products (features), can then be attributed primarily to *preference*, rather than perception. Countries that produce and consume more of a particular style of music, for example, would also reflect their preferences for those styles. These differences in musical styles can be quantified in terms of low-level musical features, which should differ across cultures in a consistent manner. Thus, music features may offer a standardized way to quantify the cultural affordances behind these preferences, without low-level confounds that comparisons of text-based cultural products may face (e.g., differences in translation or language structures). Accordingly, the present research starts with data-driven analyses on cultural products (i.e., music features) to generate novel theories involving sociocultural affordances for music preference, that are later examined by theory-driven approaches.

How Does Music Preference Reflect Emotions Across Cultures?

Schäfer and Sedlmeier (2009) found that individuals' music preferences were attributable to music's functional ability to regulate/influence participants' affective states. Yet, desired affective states are not equivalent across societies and cultures: Affect Valuation Theory (AVT) argues that individuals are motivated to seek affective experiences that match their preferences for ideal affect: emotions that people ideally want to feel (Tsai, 2017). Accordingly, this impacts cultural variations in music preference. Generally, Westerners prefer high-arousal positive (HAP) emotions (e.g., excitement, elation) and East Asians prefer low-arousal positive (LAP) emotions (e.g., calm, serenity), and this extends to preferred arousal levels in music. Tsai et al. (2007: Study 4) found that when asked to select music to listen to by themselves in preparation for a later cooperative building task, those in Hong Kong were more likely to choose music that had lower arousal descriptions, while Caucasian-Americans were more likely to choose music that had higher arousal descriptions. This is consistent with cross-cultural research on composite Spotify features that indicated arousal: users residing in Asia tended to play songs that had lower arousal than users residing in Oceania, Europe, and the Americas (Park et al., 2019).

The preference for high HAP emotions in Western societies is consistent with a greater trend of affordance for HAP and HAN emotions that are prevalent in these societies. For example, Western cultures that are typically individualistic and independent, foster socially disengaging emotions like pride or frustration (Kitayama et al., 2006) that are usually high-arousal (Lim, 2016). By contrast, collectivistic, interdependent societies may prioritize social harmony, thereby favoring socially engaging emotions like guilt or sympathy, which are usually low-arousal (Kitayama et al., 2006).

In sum, preferences and prevalence for high-arousal emotional states in the West seem congruent with high-arousal music preferences. However, to the best of our knowledge, comparatively less research has sought to understand the reasons behind this phenomenon: how does high-arousal music preference relate to cultural affordances for high-arousal emotions? One possibility could be that high-arousal music directly induces the desired HAP emotion, implying that listeners use music as mechanisms to upregulate HAP emotion. Additionally, this could also reflect the downregulation of high-arousal negative (HAN) emotions: cultures with social norms that encourage HAP emotions also tend to accept displays and experiences of HAN emotions. Consequently, these HAN emotion states are cathartically released by listening to matching high-arousal music (i.e., discharge regulation: Saarikallio, 2012; Sharman & Dingle, 2015). For collectivistic cultures that prefer low-arousal music, such high-arousal regulatory mechanisms may not be as relevant, as initial evidence suggests that emotion regulation by music occurs through low-arousal relaxation and comfort-related mechanisms instead (Saarikallio et al., 2021). We propose that elucidating these mechanisms could aid our understanding of music preference as a reflection of sociocultural affordances for emotions. These studies have also focused primarily on emotion-arousal as an avenue for cultural influences, but music may also reflect other aspects of emotion through cultural mechanisms.

The Present Research

We thus needed to start with an exploratory approach to understand broad links between music, emotion, and culture. In this article, five studies were conducted to investigate the aspects of music preferences, defined primarily by features, that reflect sociocultural differences and affordances for emotion. Study 1 examined music features from music produced within cultures, reflecting the individual's (producer) esthetics for music making. Studies 2 and 4 used music features from songs in the Top 50 charts, reflecting the collective preferences for music within a culture. For generalizability, we also examined music preferences from self-reported ratings (Studies 3 and 5). Our research structure is as follows: Studies 1 and 2 identified music features that reliably differed across cultures for theory generation. Studies 3–5 refined that theory and tested potential underlying mechanisms. This allowed us to identify features that reliably reflected regional differences in cultural affordances for emotions, which would be narrowed down by the theory generation Studies 1 and 2.

Exploring Cultural Differences in Music Features

Study 1

We compared musical features in popular music that were produced predominantly by either the United States (West) or Japan (East). As cultural products, music that is locally produced should reflect that culture's preferences as indicative of broader societal trends (e.g., Golder & Macy, 2011). We used machine learning classification (gradient boosted decision trees [GBDTs], Friedman, 2001) on data from Spotify (total $N = 1{,}006{,}644$ songs) based on a final list of artists (Japan = 2,515; United States = 1,834) obtained from Spotify's recommendation systems on initial Top 50 playlists. We classified songs as produced by Japanese or Western[1] artists based on all 13 features from Spotify's application programming interface (API; see Table 1). Feature importance was evaluated using relative variable importance (RVI) and partial dependence plots (PDPs; Friedman, 2001). Our goal was to identify features from the RVI list that could explain United States–Japan differences in terms of affect.

Table 1

A List of Song-Level Audio Features Obtained From Spotify (https://developer.spotify.com/documentation/web-api/reference/tracks/get-audio-features/)

Audio feature	Description
Duration	The duration of a song (ms).
Key	The estimated main key of a song.
Mode	If a song is major or minor (in modality).
Time signature	The estimated main time signature of a song.
Acousticness	A confidence measure on whether a song is acoustic.
Danceability	The suitability of a song for dancing. This is based on several musical features, such as tempo, rhythmic stability, regularity, and beat strength.
Energy	A measure of the intensity and activity of a song. This is based on several musical and spectral features, such as dynamic range, loudness, timbre, onset rate, and entropy.
Instrumentalness	A confidence measure of whether a song contains no vocals.
Liveness	A confidence measure on the presence of audiences in the recording.
Loudness	The overall intensity of the song in decibels (dBFS).
Speechiness	A confidence measure on the presence of spoken words (e.g., audiobooks) in a song.
Valence	An estimate of whether a song conveys positive or negative affect.
Tempo	The estimation of the main tempo of a song.

Method and Analysis

Study 1 was conducted on Spotify data using the Spotify (Thompson et al., 2019) wrapper for the Spotify API, and a total of $N = 503{,}322$ Japanese songs and $N = 678{,}218$ Western songs (later down-sampled to $N = 503{,}322$ songs for balanced comparison) were collected. This was based on a list of artists (Japan = 2,515; Western = 1,834), determined via a pseudo-snowball sampling strategy: where Spotify's recommendation systems on initial Top 50 playlists from Japan and the United States were repeatedly used for up to three iterations (two for the United States), and non-Western/non-Japanese artists were manually removed from the respective data by the authors. All songs released before 2010 were excluded, and duplicate songs (such as in rereleases or compilation albums) were removed based on Spotify track identifiers (ID). A list of artists, genres, songs, and release years are available in our OSF repository. Japanese songs were obtained in July 2020, and Western songs were obtained in November 2019.

For each song, a list of scores for various musical features was obtained from Spotify's API. Here, we note that in the list of publicly available features provided by Spotify, most were low-level features (e.g., duration, loudness, tempo), some were composites of a number of low-level features (e.g., danceability, energy), and some comparatively high-level estimates (e.g., valence) were likely confidence measures determined through predictive (machine learning) algorithms previously trained on expert ratings (Van Buskirk, 2013), and are more of an approximation of the variable of interest.

To increase the robustness and generalizability of our exploratory findings, we used a machine learning approach (GBDT). The Spotify features were entered as predictor variables, and the cultural membership of the song (Japanese or Western) was entered as the outcome variable in a binomial classification model. Using the validation set approach (see James et al., 2013), we divided our data into training and testing sets along a 3:1 ratio. All predictor variables were mean-centered and standardized. A model was first developed on the training set using GBDTs, before generating a set of predicted outcomes (classification to Western or Japanese) based on the predictor variables of the testing set. These predicted outcomes were then compared to the actual scores of the testing set, for a measure of prediction accuracy as an indicator of the predictive power of the model. A high accuracy score would suggest that the model is capable of predicting if a song was Japanese or Western based on its Spotify features, which would imply that strong differences exist between both groups from within the predictor variables.

GBDT refers to a decision tree-based ensemble method for machine learning that utilizes sequential iterations of multiple decision trees. In this method, successive trees are fitted to minimize the residuals, resulting in a model that is often capable of high-accuracy predictive learning. For more information on GBDTs, see Friedman (2001). To minimize the risk of overfitting while training the model, we used fivefold cross-validation on the training set to determine the optimum parameters: number of decision trees in the ensemble (n trees) and the interaction depth (orders of interactions allowed in each tree). This resulted in the following parameters: n trees = 150, interaction depth = 3. All procedures were conducted in R

[1] Artists collected from the US charts were considerably more diverse in cultural origin, but still mainly from Western, predominantly English-speaking cultures.

(R Core Team, 2017), using the "caret" wrapper (Kuhn, 2008) for the "gbm" package (Greenwell et al., 2019). The analysis scripts are also available in our OSF repository.

Results and Discussion

The model achieved a moderate accuracy of 0.76, 95% CI [0.75, 0.76], area under the curve = 0.83,[2] above a no information rate of 0.5: the predicted classifications matched well with actual cultural membership in the testing set. This suggested the existence of systematic differences within the data in differentiating between Japanese and Western songs on Spotify-based music features. In interpreting the model, we checked the RVI of each predictor in the model (in OSF). RVIs indicate the number of times (percentage) a predictor is chosen for stratification from all the individual decision trees in the model, as a measurement of the importance of that feature in contributing toward the model's accuracy. We focused on predictors that had RVIs of more than 10.0, as these indicated comparatively stronger effects: "speechiness" (RVI = 17.9), "duration" (RVI = 17.1), "instrumentalness" (RVI = 16.4), "danceability" (RVI = 12.5), and "energy" (RVI = 12.0). An estimate of their differences across cultures can be inferred through the PDPs in Figure 1. PDPs visualize the effect of a single predictor on the logit probability of the classification (outcome variable) from the model, while holding all other predictor variables constant. The descriptive means and standard deviations of the predictor variables are also included in our OSF repository.

Our goal was to identify features that could potentially indicate cultural affordances for affect from the RVI list that could explain the United States–Japan differences. We evaluate features from the RVI list on the basis of their possible theoretical links to emotion, but acknowledge that emotion is just one approach to examine cultural differences in music. Of the selected feature set, danceability and instrumentalness had the most accessible explanations grounded in emotion-arousal. Danceability, a composite feature quantifying rhythmic salience, was higher in American than Japanese music, and could be indicative of HAP valuation and corresponding upregulation, or HAN downregulation (Sharman & Dingle, 2015). To a smaller extent, Japanese preferred music that was higher in instrumentalness compared to Americans, suggesting that popular music produced by Japanese artists may have had stronger instrumental elements. Instrumental music (e.g., classical music) often has a calming, relaxing effect on the listener, reducing negative emotions (NEs; such as anxiety and stress; Labbé et al., 2007) through solace or distract regulation strategies (Saarikallio, 2012). This would be consistent with AVT, in that East Asians prefer LAP emotions. Energy, which encompasses a variety of different low-level features like spectral density, intensity, and entropy, can also be seen as linked to arousal, but was excluded from further analysis in this article due to the vagueness in Spotify documentation and difficulties with defining it.[3] Duration and speechiness did not appear to be related to emotion and were excluded from this interpretation.

Music features quantify the styles and types of music, and their variation across cultures signify that the styles of music produced are different between these cultures. However, what is produced in a culture may not necessarily be what is widely consumed in that culture (see Liew, Mishra, et al., 2022). To examine if the sociocultural affordances (such as function, Schäfer & Sedlmeier, 2009) for music preference underlay the current findings (on music produced), we would expect consistent differences to be found also in the (preferred) music listened to by these cultures, as measured by their respective top charts.

Study 2

Study 2 used a more generalized Western (United States, United Kingdom, Canada, Australia)–East Asian (Japan, Taiwan, Hong Kong, Singapore) cultural comparison ($N = 800$ songs) from official Spotify Top 50 charts. Charts are frequently used in cultural product research (e.g., Pérez-Verdejo et al., 2021) as they function as selection processes that capture the prevalent musical preferences of a culture. Following Study 1's results, we hypothesized that East Asian charts would have higher instrumentalness, but Western charts would have higher danceability. Using charts from Spotify also ensured consistency in the ranking mechanics regardless of country.

Method and Material

Songs were obtained from the Spotify Top 50 Playlists (charts) for four East-Asian cultures (Japan, Taiwan, Hong Kong, Singapore) and four Anglo-Western cultures (United States, United Kingdom, Canada, Australia). Data were obtained at two time points 5 months apart (December 2018 and April 2019) for a total N (songs) = 800. All data were obtained through the Spotifyr package in R. All material (data set and Jamovi analysis files) are available in our OSF repository. Pairwise comparisons were conducted using Student's t testing for danceability, and Mann–Whitney U testing for instrumentalness, due to the violation of normality assumptions.

Results and Discussion

The pattern of results from Study 1 was replicated for danceability. Danceability scores were significantly higher in Western than East Asian charts ($t(798) = -7.49$, $SE = 0.01$, 95% CI [−0.099, −0.058], $p < .001$, $d = -0.53$). However, instrumentalness was inconsistent as it significantly differed between cultures in the opposite direction from Study 1: instrumentalness was significantly higher in Western than in East Asian charts ($U = 71{,}629$, [−0.00005, −0.00003], $p < .001$, $d = -0.17$). This raises the possibility that it was a result of sample bias in Study 1, such as an oversampling of instrumental music (e.g., soundtracks) from Japan, which could be specific to the Spotify platform. As danceability was also easy to define and based on a larger body of previous research, we thus decided on examining danceability and its usefulness as a distinguishing feature of music preferences between cultures.

Theory Generation: Danceability and Cultural Differences in Affect

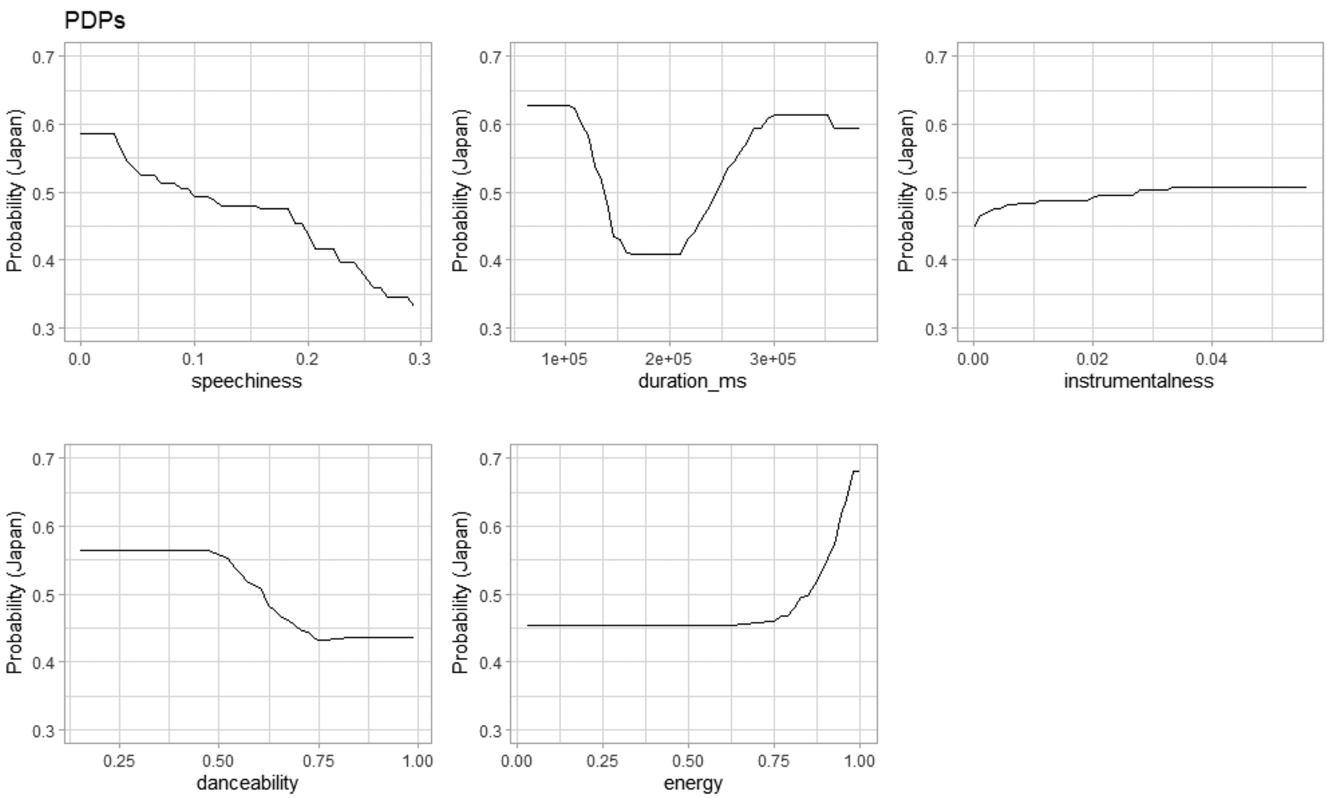
Our findings from the exploratory section revealed danceability as a suitable differentiating feature between Western and East Asian musical preferences in accordance with affect-based affordances.

[2] An AUC score of 0.83 would be approximately Cohen's $d = 1.37$ or an odds-ratio = 11.5 (Salgado, 2018), for correct (true positive/true negative) versus incorrect classifications.

[3] For an updated discussion on how energy differs from danceability in representing culturally-based affect, see Liew, Uchida, et al. (2022).

Figure 1

Partial Dependence Plots Indicate the Relationship Between Each Music Feature and Culture, in Computing the Unidirectional Classification Probability of Songs as Japanese (1) or Western/United States (0) Across the Range for the Target Feature, with all Other Features Held Constant



Note. The bottom left panel, for example, shows that higher danceability was more predictive of a song being Western than Japanese. PDP = partial dependence plots.

Danceability measures the rhythmic salience of a song, which tends to be universally perceived as high-arousal and associated with dance activities (Mehr et al., 2019; Savage et al., 2015). Dance itself is also a high-arousal activity (Bernardi et al., 2017), and has been shown to enhance positive emotional experiences with "happy" music (Christensen et al., 2014). Accordingly, we predicted that danceability in music reflects the extent to which high-arousal emotions were valued or experienced in various cultures. While the research primarily focuses on music features, in this section, we also quantify music-emotion preferences through self-report surveys for a more holistic examination.

Study 3

Following our hypothesis, cross-cultural differences in danceability, and by extension, arousal, should also be present in other forms of measurement. Study 3 examined individual levels of cross-cultural differences in arousal and dance preferences through investigating music functions and preferences via a questionnaire study on Singaporean ($N = 127$) and American ($N = 141$) undergraduates.[4] As functions of music are closely related to music preferences (Schäfer & Sedlmeier, 2009), both affect preference and music-listening functions should reflect the mechanisms predicted by danceability in a consistent manner: (a) preferences for (positively and negatively valenced) high-arousal music should be stronger in the United States than Singapore; (b) individuals in the United States would prefer more dance functions, but individuals in Singapore should prefer low-arousal regulatory functions (i.e., mood regulation). Past research has elaborated on the link between affect and independent-interdependent self-construal, so we also examined cultural effects through self-construal at the individual level. Given that the United States is typically more independently oriented than East Asia (including Singapore; Markus & Kitayama, 1991), we posit that (c) individuals with higher independent orientation would use music for more dance functions and prefer high-arousal music.

Music listening may not always be a main activity, in that recreational music listening is rarely devoid of secondary tasks or distractions, often accompanying other activities, like working, studying, or driving (Krause & North, 2014; Sloboda & O'Neill, 2001). Accordingly, we examined music preferences for arousal in music in two contexts. Participants were asked to create an imaginary playlist for the context of "relaxing" and "studying," corresponding to active versus background listening, respectively. Participants then

[4] Sample size was limited by the availability of the student sample in Singapore, and the US sample size was set to match the Singapore sample.

rated the arousal for these playlists, and provided information on musical reward styles and cultural self-construal. However, as reported in the Results section, an equivalence test showed arousal ratings across both contexts to be equivalent, so scores were averaged into a single measure for arousal.

Procedure

An online questionnaire (in English) was administered to 268 participants (Singapore: $N = 127$, $M_{\text{age}} = 21.4$, $SD = 1.8$, Females = 93, Males = 34; United States: $N = 141$, $M_{\text{age}} = 20.0$, $SD = 2.4$, Females = 105, Males = 33, Others = 3) who were recruited from respective undergraduate participant pools in Singapore (National University of Singapore) and the United States (Arcadia University) for course credit. Participants from Singapore completed the web-based questionnaire on their own time and participants from the United States completed the questionnaire within the psychology laboratories on campus. This study obtained approval from the respective institutional ethics review committees.

Material

To examine arousal levels of music preferences, participants were asked to create an imaginary playlist for the context of "relaxing" and "studying," that measured different aspects of music listening: attended recreational listening (relaxing) and unattended background listening (studying). Following this, they were asked to rate each playlist on a list of 24 descriptors (see North & Hargreaves, 1996). Following stable factor structures identified by Krause and North (2018), these descriptors were then grouped into three latent factors: arousing (attention-grabbing, invigorating, loud, exotic, can dance vigorously to it, exciting/festive, and strong rhythm), serene (beautiful, inspiring-majestic, natural-fresh, romantic, and relaxing-peaceful), and melancholy (sad and moody). For the purpose of our study, we assumed the arousing factor to reflect high-arousal preferences.[5] Participants also completed the Barcelona Music Reward Questionnaire (Mas-Herrero et al., 2013), which consists of five facets of possible rewards from music listening: emotion evocation (HAP emotion), mood regulation (low-arousal affect regulatory functions), social reward (prosocial functions), sensory motor (dance-tendencies), and musical seeking (music enjoyment). Finally, participants provided other information pertaining to cultural self-construal (Singelis, 1994) and demographics (age, gender, and everyday music listening habits). Participants in Singapore also completed questionnaires on social withdrawal and subjective well-being for a different research project.

Results and Discussion

Descriptives and full results are in the OSF repository. Using a "two one-sided test" of equivalence with $\alpha = .05$, and equivalence bounds (smallest effect size of interest) of Cohen's $d = 0.3$, we noted no significant differences in arousing scores between the "relaxing" and "studying" contexts, $t(534) = -1.39$, $p = .166$, and that the 90% CI was fully contained within the equivalence interval—upper: $t(534) = -4.9$, $p < .001$; lower: $t(534) = 2.1$, $p = .019$, suggesting that the arousing scores between the "relax" and "studying" context were not significantly different and statistically equivalent. Accordingly, for the rest of the analyses, these scores were averaged for a single "arousing" score that represented both contexts.

One-way analyses of variance (ANOVAs) were conducted to examine cultural differences for arousal, music reward, and independence/interdependence. A significant difference was found for arousing, $F(1, 236) = 5.53$, $p = .019$, $\omega^2 = 0.017$, and sensory motor, $F(1, 266) = 20.6$, $p < .001$, $\omega^2 = 0.068$ with post hoc tests revealing significant differences (Tukey HSD) for sensory motor ($t(266) = -4.53$, $p < .001$) and arousing ($t(266) = -2.35$, $p = .019$). U.S. participants preferred dance functions of music more than Singaporean participants, and they also preferred more arousing music. Post hoc power analyses using G*Power (Faul et al., 2007) reveal an observed power = 0.64 ($f = 0.14$, $\alpha = .05$) for arousing and power = 0.99 ($f = 0.28$, $\alpha = .05$) for sensory motor. No other significant differences were observed. This supports our first hypothesis that U.S. participants preferred high-arousal music and dance functions.

With culture, age, and gender as controls, we examined the effect of independence on music emotion and function. Again, we report only significant effects, but the full results are available in our OSF repository. Independent self-construal significantly predicted arousing ($b = 0.09$, $SE = 0.05$, 95% CI [0.001, 0.18], $t = 2.00$, $p = .047$); social reward ($b = 0.03$, $SE = 0.02$, [0.003, 0.07], $t = 2.14$, $p = .033$); sensory motor ($b = 0.07$, $SE = 0.02$, [0.04, 0.11], $t = 4.08$, $p < .001$); musical seeking ($b = 0.03$, $SE = 0.02$, [0.001, 0.06], $t = 2.06$, $p = .041$); and mood regulation ($b = 0.03$, $SE = 0.01$, [0.003, 0.06], $t = 2.21$, $p = .028$). In short, across cultures, independent individuals preferred more arousing music, and were more likely to listen to music for social reasons, dance, enjoyment, and mood regulation. Interestingly, listening to music for intense emotional experiences (emotion evocation) was not more prevalent in the United States than Singapore, nor higher in independently oriented (than interdependently oriented) individuals, suggesting that musical HAP upregulation may not significantly reflect cultural differences for HAP emotions. Also, listening to music for low-arousal mood regulation purposes was not significantly stronger in Singapore than the United States, which suggests that low-arousal listening may not differ between cultures as strongly as high-arousal listening.

Independent orientation appeared to predict music preference in the direction that we initially anticipated (e.g., arousal; sensory motor/dance). Yet, despite known cultural differences in self-construal (e.g., Wee et al., 2021), the United States did not score higher than Singapore on independence, possibly due to the reference group effect (Heine et al., 2002): this underrepresents cultural-level differences in independence and interdependence when measured at the individual level. Moreover, self-construal showed poor measurement invariance across cultural groups (see the online supplemental material in our OSF repository). Accordingly, we needed additional measures to examine if independence, at a macro/cultural level, would show a relationship with danceability across countries.

Study 4

A macro-level cross-cultural comparison study was conducted to address the following concerns: Firstly, we elucidate relationships

[5] We did not use the Serene and Melancholy factors, as given our interest in arousal, the individual emotion terms in the Serene factor showed differing arousal patterns (e.g., inspiring-majestic and romantic descriptors may imply high-arousal emotional experiences), and Melancholy was additionally confounded by a clear negative valence.

between danceability, affect, and independent orientation, that were found in Study 3. Studies 1–3 relied on dichotomous East–West cultural comparisons, that are not sufficiently representative of global variation in cultural contexts and values (Triandis, 1995). Furthermore, effects in Study 3 were observed at a participant level, which may not necessarily generalize to cultural-level effects. A macro-level cross-cultural study was thus needed to investigate if country-level relationships on music preferences support our hypotheses on danceability as reflective of cultural affordance for emotion and independence (from Study 3). To measure cultural variation in independence, we used two commonly used indices that encompass independent self-construal at the country level: individualism–collectivism and tightness–looseness. Tightness–looseness measures the strength of social norms, and residents of "tight" cultures often have higher impulse control and cautiousness than "loose" cultures (Harrington & Gelfand, 2014) that overlap with interdependent orientations. Similarly, collectivistic societies value social aspects of society, like family integrity, that encompass interdependent orientations (Triandis & Gelfand, 1998).

Secondly, we model cultural differences at a macro level to test for alternative explanations. For example, rather than our hypothesized affect regulation and independence explanations, relationships between culture and danceability could also be due to structural issues, such as socioeconomic status (SES). Societies with lower SESs have generally narrower music preferences (Chan & Goldthorpe, 2006). One possibility could be through limited channels of access to global or new music, which may in turn drive preference for homegrown, localized music. Accordingly, cultures with wider income gaps (income inequality) may show more diverse preferences, which may manifest in danceability scores. Geopolitical and historical reasons could also play a role: if certain cultures are historically more linked toward dance music, these could spread within their spheres of political or cultural influence, for example, through colonialization, migration, or investment inflows and outflows. By including these variables as covariates in the model, we can also test the robustness of the danceability and affect hypotheses above and beyond these alternative explanations.

Finally, we included additional measures of danceability with open-source documentation. Without a publicly released computational breakdown of Spotify's danceability, we are unable to adequately define danceability, and future research targeting specific aspects of danceability may have difficulty with interpreting, replicating, and reproducing this line of research. As such, we included two other measures of danceability in this study. These were based on open-sourced danceability models from the *Essentia* (Bogdanov et al., 2013) audio-analysis library, that were executed on the audio files for all songs in the data set. We hope to demonstrate that these findings are robust across measures of danceability, and to facilitate future research on specific components of danceability and culture.

We used Top 50 playlist information from 60 countries that Spotify operated in to obtain scores for danceability, and combined these song-level data with country-level data. Our priority was to establish a link between individualism, positive and negative affect, and danceability at a country level. Subsequently, we examined the robustness of these relationships amid the inclusion of covariates for colonialization, trade, migration, political structure, and income inequality. We finally examined the robustness of the danceability construct, by comparing Spotify's scores for danceability with scores from two other open-sourced models of danceability.

Measures

Scores for danceability were obtained from 60 countries that had access to Spotify (at the point of data collection in December 2018). As with Study 2, Top 50 lists for each country were used to obtain songs for analysis. We combined these song-level data with country-level data for log-transformed GDP (gross domestic product) per capita, NE experience, and individualism. Scores for individualism were obtained from Hofstede's Cultural Insights (Hofstede et al., 2010), and NE and positive emotion (PE) experience, and GDP were obtained from the World Happiness Report 2019 (Helliwell et al., 2019). NE experience scores were the sample prevalence of the presence of NE experiences (averaged score of anger, worry, and sadness) experienced by participants on the preceding day. This was similar to positive emotional experience for happiness, laughter, and enjoyment. GDP was obtained from log-transformed 2018 or 2017 GDP per capita where applicable. We also obtained scores for migration (immigrants as a percentage of the population) in 2015, Gini coefficients (for income inequality) from 2016, 2017, or 2018 where applicable, foreign direct investment (FDI) inflows and outflows (as a percentage of GDP) in 2019, and various governance indicators (rule of law, political stability, regulatory quality, accountability, and corruption control) from the World Bank Database. Domain-general scores for cultural tightness–looseness were obtained from Uz (2015), and the colonial history of a country was obtained from the International Correlates of War (ICOW) data set (Hensel & Mitchell, 2007).

For additional estimations of danceability, we used the *danceability* (Streich & Herrera, 2005) and *danceability-musicnn-mtt* (Correya et al., 2021) models from the Essentia library. The former estimates danceability through detrended fluctuation analysis (DFA), a low-level acoustic/audio feature that tracks the stability and strength of the beat of a song. The latter uses predictions from a convolutional neural network (CNN) model, trained initially through "danceable" tags from the MagnaTagATune data set (Law et al., 2009; see Pons & Serra, 2019). These are high-level probability scores, that are predicted by a deep learning model previously trained on human annotations of "danceable" music, and may not necessarily map on to low-level acoustic features of music. These estimates were applied on the raw audio files for songs belonging to the Top 50 playlists. We used string matching (Levenshtein's distance) to match the Spotify artist names and song titles, with recorded artist names and song titles from the Deezer music catalog, and manually confirmed the match. Scores for *danceability* (DFA danceability) and *danceability-musicnn-mtt* (CNN danceability) were computed and provided by Deezer with the *Essentia* models. All country-level data are publicly accessible in our OSF repository.

Results

Danceability Correlations

We first examined correlations between Spotify's and Essentia's versions of danceability at the song level. After removing duplicate songs, we counted $N = 945$ unique songs. Spotify's danceability was positive and significantly correlated with both CNN danceability, $r = .62$, 95% CI [0.58, 0.65], $p < .001$, and DFA danceability, $r = .51$, [0.46, 0.55], $p < .001$, and CNN danceability and DFA danceability were also similarly correlated, $r = .52$, [0.47, 0.56], $p < .001$.

Affect, Individualism, and Tightness

Spotify Danceability. We examined these three effects in a series of random-intercept mixed regression models. Confidence intervals were calculated using Wald's method, and degrees of freedom were estimated using Sattertwaith's method in jamovi (The Jamovi Project, 2020). Note that, as the number of countries included in each regression analysis differed according to the data set we used, we were generally unable to compare differences between models through commonly used fit indices. For this reason, we were conservative about the inclusion of variables in each model, to maximize the sample size of the data set. For affect, we fitted a model predicting Spotify's danceability at the song-level (see Table 2: Model S1) and country-level predictors of PE and NE experience, and controls for log-transformed GDP per capita (country-level SES). With $N = 61$ countries, a restricted maximum likelihood (REML) model ($R^2_{\text{Marginal}} = 0.072$, $R^2_{\text{Conditional}} = 0.153$) showed a significant effect of NE, but not PE nor GDP per capita. We then fitted a second model (Table 2: Model S2) that included an addition of Hofstede's country-level scores for individualism to the model above. With $N = 60$ countries, a REML model ($R^2_{\text{Marginal}} = 0.073$, $R^2_{\text{Conditional}} = 0.152$) showed a significant effect of NE, but not individualism, PE, or GDP per capita.

We then fitted a separate model (Table 2: Model S3) using country-level scores for tightness–looseness (Uz, 2015), that also reflect independence-interdependent social norms, and corresponding emotional expression for PE and NE (Liu et al., 2018). NE, PE, and GDP per capita were also included as covariates. Using Uz's (2015) domain-general estimations of tightness–looseness from $N = 34$ countries that had Spotify data available (from our data set), a REML model ($R^2_{\text{Marginal}} = 0.064$, $R^2_{\text{Conditional}} = 0.117$) showed a significant effect of tightness–looseness, and NE. No significant effects were observed for PE, and GDP per capita.

Essentia Danceability. We then replicated the affect and tightness–looseness models with DFA danceability and CNN danceability. For DFA danceability, the affect (NE, PE, and GDP per capita) model (Table 2: D1; $N = 61$ countries; $R^2_{\text{Marginal}} = 0.122$, $R^2_{\text{Conditional}} = 0.264$) revealed a significant effect of NE, PE, and GDP per capita. However, with the inclusion of tightness–looseness (Table 2: D2), no significant effects were found ($N = 34$ countries; $R^2_{\text{Marginal}} = 0.037$, $R^2_{\text{Conditional}} = 0.174$) for tightness–looseness, NE, PE, and GDP per capita.

For CNN danceability, the affect (NE, PE, and GDP per capita) model (Table 2: C1; $N = 61$ countries; $R^2_{\text{Marginal}} = 0.078$, $R^2_{\text{Conditional}} = 0.203$) revealed a significant effect of NE, but not PE or GDP per capita. With the inclusion of tightness–looseness, (Table 2: C2; $N = 34$ countries; $R^2_{\text{Marginal}} = 0.037$, $R^2_{\text{Conditional}} = 0.174$) we found similar results to the original Spotify measure: CNN danceability was significantly predicted by tightness–looseness, and NE. No significant effect was observed for PE and GDP per capita.

In sum, we found a robust effect of NE: the higher a country's NE score, the higher the danceability of its Top 50 popular songs. Even when controlling for tightness–looseness and individualism across different estimation methods for danceability, this relationship was largely observed. In contrast, PE showed only localized effects in specific

Table 2
Significant Effects for Regression Models Predicting Danceability

Danceability	Model	Terms	*b*	*SE*	95% CI *LL*	95% CI *UL*	*df*	*t*	*p*
Spotify	S1								
		NE	**0.41**	**0.10**	**0.21**	**0.60**	**57.0**	**4.10**	**<.001**
		PE	0.13	0.07	−0.002	0.26	57.0	1.93	.058
		GDP	−0.02	0.01	−0.04	0.0008	56.8	−1.88	.066
	S2^								
		NE	**0.41**	**0.10**	**0.23**	**0.60**	**57.1**	**4.10**	**<.001**
		Individualism	−0.00005	0.0003	−0.001	0.0001	54.8	−1.45	.154
	S3^								
		NE	**0.26**	**0.11**	**0.05**	**0.48**	**29.1**	**2.42**	**.022**
		Tightness–looseness	**0.001**	**0.003**	**0.0005**	**0.002**	**28.9**	**4.10**	**<.001**
Essentia—DFA	D1								
		NE	**0.39**	**0.14**	**0.11**	**0.67**	**56.9**	**2.75**	**.008**
		PE	**0.27**	**0.09**	**0.09**	**0.46**	**56.9**	**2.93**	**.005**
		GDP	**−0.04**	**0.01**	**−0.07**	**−0.01**	**56.8**	**−2.94**	**.005**
	D2^								
		Tightness–looseness	0.0006	0.0004	−0.0001	0.001	28.9	1.49	.147
Essentia—CNN	C1								
		NE	0.96	0.26	0.44	1.47	57.1	3.63	<.001
		PE	0.33	0.17	−0.01	0.67	57.0	1.93	.063
		GDP	−0.04	0.03	−0.09	−0.01	56.9	−1.45	.151
	S3^								
		NE	**0.74**	**0.29**	**0.17**	**1.31**	**29.1**	**2.54**	**.017**
		Tightness–looseness	**0.003**	**0.0007**	**0.003**	**0.004**	**29.0**	**4.12**	**<.001**

Note. Covariates are only reported for base models, and only significant effects and new terms are reported for subsequent models (marked by a "^"), but outputs of full models are available in our OSF Repository. Bold values indicate statistical significance, $p < .05$. CI = confidence interval; *LL* = lower limit; *UL* = upper limit; NE = negative emotion; PE = negative emotion; GDP = gross domestic product; DFA = detrended fluctuation analysis; CNN = convolutional neural network.

conditions. We also found that tightness–looseness, and not individualism, predicted danceability across cultures: countries with higher danceability scores in their Top 50 songs also had looser social norms.

Additional Covariates

Income Inequality. We added the Gini coefficient (at a country level) into the model, alongside covariates for NE, PE, GDP per capita, and tightness–looseness. In the model (Table 3: II-S; $N = 31$ countries; $R^2_{\text{Marginal}} = 0.09$, $R^2_{\text{Conditional}} = 0.116$), the Gini index and tightness–looseness, showed significant effects in predicting danceability, but no significant effects were observed for NE, PE, and GDP per capita. Using the DFA danceability measure, the model (Table 3: II-D; $N = 31$, $R^2_{\text{Marginal}} = 0.078$, $R^2_{\text{Conditional}} = 0.180$) showed a significant effect of income inequality, but no significant effects were observed for NE, PE, tightness–looseness, and GDP per capita. Finally using the CNN danceability measure, the model ($N = 31$ countries, $R^2_{\text{Marginal}} = 0.117$, $R^2_{\text{Conditional}} = 0.174$) resembled the Spotify danceability model, in showing a significant effect of income inequality, and tightness–looseness, but no significant effects were observed for NE, PE, and GDP per capita.

In sum, countries with greater income inequality have the Top 50 songs with higher danceability scores. Depending on the measure of danceability, despite the inclusion of the Gini index into the regression model, tightness–looseness still significantly predicted danceability. However, NE no longer significantly predicted danceability across all three estimates. Our interpretation is that countries with high-income inequality would also have greater affordance for NEs (country level; Pearson's $r = .53$, 95% CI [0.28, 0.71], $p < .001$), which can be reflected through greater consumption of danceable music (Table 3).

Colonial History, Migration, FDI Inflows/Outflows, and Governance. Next, we examined if the cultural variation in danceability could also be predicted by geopolitical and historical factors. First, we examined colonial history: countries may be influenced by the lasting values, trends, and esthetics of their colonial past, where countries with similar colonial histories may share preferences for certain types of music, that may then be reflected in danceability preferences. As there were 19 levels for this variable, we report only the significant effects in this section. The full results are available in our OSF repository.

Overall, the model fitted to Spotify danceability scores ($N = 57$ countries; $R^2_{\text{Marginal}} = 0.140$, $R^2_{\text{Conditional}} = 0.171$) with covariates for PE, NE, and GDP per capita (tightness–looseness was removed from the model due to its reduced sample size of 31 countries), revealed a significant effect of NE. No significant effects of PE and GDP per culture were observed. As colonial history was deviation coded, we observed a significant effect of colonizer for Brazil, Central America, Colombia, Czechoslovakia, Haiti, Russia, Spain, Sweden, and the United States. In sum, compared to the mean across all levels, the Top 50 songs from countries that were historically colonized by Brazil, Central America, Colombia, Haiti, and Spain had higher danceability, and the Top 50 songs from countries colonized by Czechoslovakia, Russia, Sweden, and the United States had lower danceability. Countries with no colonization history also had significantly lower danceability than the average. Even after controlling for this effect, NE significantly predicted danceability (Table 4). Due to space constraints in the manuscript, results from the DFA and CNN danceability models are in our OSF repository.

We also examined the proportion of migrants within a population, as well as FDI inflows and outflows of a country, relative to GDP. GDP per capita, NE, and PE were included in the model with Spotify danceability scores ($N = 57$ countries; $R^2_{\text{Marginal}} = 0.076$, $R^2_{\text{Conditional}} = 0.164$). Aside from NE ($b = 0.37$, $SE = 0.11$, 95% CI [0.14, 0.59], $t(50.0) = 3.24$, $p = .002$), no other significant effects were observed. We then fitted a model with governance indicators (rule of law, political stability, regulatory quality, accountability, and corruption control) with GDP per capita, NE, and PE, but only NE significantly predicted danceability ($b = 0.28$, $SE = 0.13$,

Table 3
Effects for Income Inequality in Predicting Danceability

Danceability	Model	Terms	*b*	*SE*	95% CI *LL*	95% CI *UL*	*df*	*t*	*p*
Spotify	II-S								
		NE	0.11	0.10	−0.07	0.30	24.9	1.18	.247
		PE	0.05	0.06	−0.06	0.16	25.0	0.91	.371
		GDP	0.01	0.02	−0.01	0.05	24,9	1.05	.303
		Tightness–looseness	**0.0009**	**0.0002**	**0.0004**	**0.001**	**24.8**	**3.44**	**.002**
		Gini	**0.006**	**0.001**	**0.003**	**0.008**	**24.7**	**4.09**	**<.001**
Essentia—DFA	II-D								
		NE	0.05	0.16	−0.26	0.36	25.0	0.32	.748
		PE	0.14	0.09	−0.04	0.33	25.0	1.53	.140
		GDP	0.01	0.03	−0.03	0.07	25.0	0.65	.519
		Tightness–looseness	0.0004	0.0004	−0.0004	0.001	25.0	1.06	.297
		Gini	**0.007**	**0.002**	**0.002**	**0.01**	**24.9**	**2.65**	**.007**
Essentia—CNN	II-C								
		NE	0.38	0.27	−0.16	0.92	25.0	1.39	.176
		PE	0.02	0.16	−0.29	0.34	25.0	0.15	.881
		GDP	0.07	0.04	−0.02	0.15	25.0	1.53	.142
		Tightness–looseness	**0.002**	**0.0007**	**0.0009**	**0.004**	**24.9**	**3.25**	**.003**
		Gini	**0.01**	**0.004**	**0.006**	**0.02**	**24.8**	**3.46**	**.002**

Note. Bold values indicate statistical significance, $p < .05$. CI = confidence interval; *LL* = lower limit; *UL* = upper limit; NE = negative emotion; PE = negative emotion; GDP = gross domestic product; DFA = detrended fluctuation analysis; CNN = convolutional neural network.

Table 4
Significant Effects for Colonial History Predicting Spotify's Danceability

Terms	Coloniser	*b*	*SE*	95% CI *LL*	95% CI *UL*	*df*	*t*	*P*
NE		**0.27**	**0.10**	**−0.07**	**0.47**	**34.0**	**2.66**	**.012**
PE		−0.10	0.07	−0.24	0.04	33.8	−1.35	.185
GDP		0.01	0.01	−0.01	0.03	33.9	0.97	.338
Colonial history								
	Brazil	**0.001**	**0.01**	**0.01**	**0.14**	**34.1**	**2.35**	**.025**
	Central Am	**0.09**	**0.02**	**0.05**	**0.13**	**33.8**	**4.16**	**<.001**
	Colombia	**0.08**	**0.02**	**0.03**	**0.12**	**34.1**	**3.12**	**.004**
	Czechoslovakia	**−0.07**	**0.02**	**−0.12**	**−0.03**	**33.9**	**−3.09**	**.004**
	Haiti	**0.08**	**0.03**	**0.02**	**0.15**	**34.1**	**2.72**	**.010**
	Russia	**−0.04**	**0.01**	**−005**	**−0.005**	**34.3**	**2.39**	**.040**
	Spain	**0.07**	**0.01**	**0.04**	**0.10**	**34.0**	**5.04**	**<.001**
	Sweden	**−0.11**	**0.03**	**−0.17**	**−0.05**	**34.1**	**−3.52**	**.001**
	United States	**−0.08**	**0.03**	**−0.14**	**−0.008**	**34.1**	**−2.19**	**.035**
	None	**−0.03**	**0.01**	**−0.05**	**−0.005**	**34.3**	**−2.39**	**.023**

Note. Full model outputs (alongside DFA and CNN danceability) are available in our OSF repository. Note that colonial history was deviation coded, comparing the mean of each level against the mean of all levels. Bold values indicate statistical significance, $p < .05$. CI = confidence interval; *LL* = lower limit; *UL* = upper limit; NE = negative emotion; PE = negative emotion; GDP = gross domestic product; DFA = detrended fluctuation analysis; CNN = convolutional neural network.

[0.03, 0.54], $t(48.8) = 2.15$, $p = .037$). Full results are reported in the OSF repository.

Discussion

Our results showed a strong and stable effect of NE experience in predicting danceability of Top 50 charts across cultures. Even when controls were included for cultural differences in values (individualism–collectivism), social norms (tightness–looseness), migration, foreign investment, and geopolitical (colonial) history, results showed that higher prevalence of NEs on a cultural level predicted the danceability of songs on their Top 50 charts.[6, 7] While association with NEs was not significant after the inclusion of income inequality, this may still be consistent in that income inequal societies also have higher prevalence of NEs.

Danceability and HAN Affect

This is further contextualized by the significant relationships between danceability and tightness–looseness (which was also robust across analyses and evident in both Spotify's and Essentia's CNN danceability estimates). Looser cultures, where social norms are less strict and displays of emotion more encouraged, prefer music with higher danceability. As dancing is often seen as an outward expression of one's emotional states (Schwender et al., 2018), music that can facilitate dancing (high danceability) would naturally be more popular in looser cultures than tighter cultures.

Our results also showed that cultures with higher prevalence of income inequality have increased danceability. Moreover, when income inequality was included in the model, the variance explained by NE experience was drastically reduced. Past research has shown that low SES creates the environment for increased NEs (Gallo & Matthews, 2003) and that income inequality is itself also associated with more NEs (Godoy et al., 2006). Accordingly, in our data, we found a similar correlation between NE experience and income inequality. Countries with higher income inequality experience more prevalent negative affect, so the corresponding relationship with danceability scores may consistently be reflective of a functional usage of music listening to downregulate these HAN emotions.

Here, our hypothesis is that danceability may be representative of tendencies to downregulate HAN affect. Societies with high-income inequality, and/or societies with loose social norms, may have more prevalent experiences of HAN emotions that result in the use of danceable music as a downregulation strategy. Yet, what role does danceability play in HAN downregulation? Given that dance is a high-arousal activity (Bernardi et al., 2017), and that danceability may quantify the level of arousal in a song, we propose that cathartic music listening for discharge regulation of HAN emotions could be the missing link, which we examine in Study 5.

Study 5

We theorized that individual in cultures where HAN emotions are more widely experienced and expressed could be cathartically listening to high-arousal, danceable music to downregulate these emotions, by matching the arousal of the listener with the arousal of the music (Sharman & Dingle, 2015). Danceability could thus reflect the HAN emotion prevalence within a culture, by representing its cultural tendencies toward discharge listening in music to downregulate it. If

[6] This was most evident in Spotify's danceability and Essentia's CNN danceability, but the comparatively lower-level DFA danceability scores were only significantly replicated in the base (positive and negative affect and GDP per Capita) model. One possibility could be that danceability, as predicted by machine learning algorithms trained on human annotations, was more sensitive and reflective of danceability as a construct. By contrast, DFA may not be as sensitive to smaller changes and minute fluctuations in danceability (Streich & Herrera, 2005).

[7] As data were collected in 2019, we updated it with a newer round of data collection following the same analysis scripts in 2022. Here, NE continued to predict danceability in the base affect models, but not in the subsequent models. Full results are available in our OSF repository. This may arise from our covariate data being outdated (i.e., several variables, like GDP and NE were obtained from 2019, despite playlists (songs) from 2022, and more research is needed to replicate and extend the findings.

so, cultures with more HAN emotion prevalence would thus engage more with discharge regulatory strategies in music listening. By contrast, cultures that do not frequently experience HAN emotions may not need discharge regulation, but can make do with solace or distract regulation methods that are better suited to downregulate low-arousal negative (LAN) states (Saarikallio, 2012).

Specifically, we hypothesized that discharge regulation would be higher in looser cultures, and associated with higher HAN emotion prevalence: HAN prevalence should mediate the relationship between culture and the usage of discharge regulation in music listening. To examine this hypothesis, we examined these tendencies at an individual participant level, and conducted a survey of $N=$ 227 adults from Japan (tight culture) and the United States (loose culture), and examined their self-reported experiences of emotions, and emotion regulation strategies (including discharge regulation) from music.

Procedure

An online questionnaire was administered to participants from Japan ($N = 116$; $M_{\text{age}} = 43.5$, $SD = 8.8$, Females = 34, Males = 81, Rather not say = 1) and the United States ($N = 111$, $M_{\text{age}} = 33.5$, $SD = 12.9$, Females = 52, Males = 53, Others = 4, Rather not say = 2), recruited from the *Lancers* (Japan: https://lancers.jp) and *Prolific* (United States: https://prolific.co) crowdsourcing platforms for ¥500 and $10.00, respectively. Participants completed the Affect Valuation Index (AVI; Tsai et al., 2007), a self-report measure that examines participants' ideal or desired emotions, and more relevantly, the actual emotions experienced over the course of a week. These were broadly grouped into four categories: HAN (e.g., fearful, hostile), HAP (e.g., enthusiastic, excited), LAN (dull, sluggish), and LAP (rested, calm), across "ideal" and "actual" emotion experiences. Next the Brief Music in Mood Regulation Scale (B-MMR; Saarikallio, 2012) was administered. We focused mainly on the discharge regulation subscale (e.g., "When I'm angry with someone, I listen to music that expresses that anger"), but additional analyses were also conducted on the diversion (e.g., "For me, music is a way to forget about my worries") and solace (e.g., "When everything feels bad, music understands and comforts me") subscales that comprised strategies toward NE downregulation. Participants provided demographic information, such as age, gender, music experience, SES, and ethnicity, and was approved by the respective Institutional Review Boards of Stanford University and Kyoto University for data collection in the United States and Japan. As the survey was administered in Japanese in Japan, we used the Japanese versions of the AVI and B-MMR (Shoda et al., 2019). Demographic questions were translated into Japanese, and then back-translated into English for checking.

Results and Discussion

After controlling for age, gender, and country, a linear regression model ($R^2 = 0.28$) showed that HAN-actual significantly predicted discharge regulation, where higher HAN-actual scores were associated with higher discharge regulation scores. Country was also significant in predicting discharge regulation (Japan as reference), where discharge regulation was stronger in the United States than in Japan. To control for possible effects of arousal and valence, we conducted a separate analysis with all four emotion terms (HAP, HAN, LAP, LAN) in the "actual" context. With controls for age, gender, and country, a linear regression model ($R^2 = 0.29$) showed than HAN-actual was still predictive of discharge regulation, as with country, in similar directions. Furthermore, HAP-actual also significantly predicted discharge regulation, albeit to a smaller extent than HAN-actual. Post hoc power analyses using G*Power (Faul et al., 2007) reveal an observed power = 0.99 ($f = 0.39$, $\alpha = .05$) for the HAN-actual model and power = 0.99 ($f = 0.41$, $\alpha = .05$) for the full (HAP, HAN, LAP, LAN) model.

Next, we examined "ideal" emotion scores. With the same controls for age, gender, and country, a linear regression model ($R^2 = 0.24$), HAN-ideal significantly predicted discharge regulation. However, when all four ideal emotions (HAP, HAN, LAP, LAN) were included in the model ($R^2 = 0.23$), no significant effects were observed for any of these terms. Regression results are summarized in Table 5. Post hoc power analyses reveal an observed power = 0.99 ($f = 0.32$, $\alpha = .05$) for the HAN-ideal model.

Finally, we examined a mediation model involving country, HAN-actual, and discharge regulation. Culture was dummy coded as Japan = 0 and United States = 1. All standard errors and confidence intervals were calculated on 1,000 bootstrapped iterations. The direct effect of country and discharge regulation was significant ($b = 2.53$, $SE = 0.47$, 96% CI [1.62, 3.48], $B = 0.33$, $Z = 5.42$, $p < .001$), and was partially mediated by HAN-actual: country significantly predicted HAN-actual ($b = 0.24$, $SE = 0.10$, 95% CI [0.05, 0.43], $B = 0.15$, $Z = 2.43$, $p = .015$), and HAN-actual significantly predicted discharge regulation ($b = 1.53$, $SE = 0.31$, [0.91, 2.12], $B = 0.29$, $Z = 4.94$, $p < .001$), for a significant indirect effect of country and HAN-actual on discharge regulation($b = 0.36$, $SE = 0.17$, [0.03, 0.69], $B = 0.05$, $Z = 2.13$, $p = .033$). This suggests a significant partial mediation effect of HAN-actual on the relationship between culture and discharge regulation. Participants in the United States were more likely to use music for discharge regulation purposes, and this effect was mediated by the amount of HAN emotions experienced subjectively over the past week. Full results (including models fitted to diversion and solace regulation) are available in our OSF repository.

Discharge regulation in music was significantly linked with participants' HAN emotion experiences, and this effect was consistent with participants' countries of origin: participants from the United States, a culture with looser social norms (Tightness–Looseness domain-general scores from Uz, 2015: 71.5) and higher income inequality than Japan (Tightness–Looseness: 39.2), were also more likely to use discharge regulation strategies. Moreover, we noticed that this effect was also true for ideal or desired HAN emotion experiences, in that participants with higher desired HAN emotions were more likely to use music for discharge regulation purposes. These are consistent with our theory that individuals from cultures with higher affordances for HAN emotions engage with music to downregulate these emotions, as affordances for HAN emotions include both the circumstances to induce these emotions in daily life, and the social acceptance for experiencing and expressing them ("actual" and "ideal" HAN, respectively). However, we also noted a smaller but significant effect of HAP-actual in predicting discharge regulation. This could be a consequence of the United States being more accepting of high-arousal emotions in general, but we hesitate on speculating on a link, given that Studies 3 and 4 did not show a consistent effect of PE experiences on music listening across cultures. Additionally, in comparing results with other regulatory styles for NE downregulation

Table 5
Effects for Base Models (HAN-Actual and HAN-Ideal), Actual Model (HAN-Actual, HAP-Actual, LAN-Actual, LAP-Actual), and Ideal Model (HAN-Ideal, HAP-Ideal, LAN-Ideal, LAP-Ideal) in Predicting Discharge Regulation

Model	Terms	*b*	*B*	*SE*	95% CI *LL*	95% CI *UL*	*t*	*p*
Base-actual								
	Country (US-JP)	**1.80**	**0.46**	**0.51**	**0.80**	**2.81**	**3.53**	**<.001**
	Age	**−0.06**	**−0.18**	**0.02**	**−0.10**	**−0.02**	**−2.89**	**.004**
	Gender (F–M)	0.05	0.01	0.48	−0.89	1.00	0.11	.912
	HAN-actual	**1.51**	**0.29**	**0.31**	**0.91**	**2.11**	**4.93**	**<.001**
Actual								
	Country (US-JP)	**1.21**	**0.31**	**0.57**	**0.08**	**2.34**	**2.10**	**.037**
	LAN-actual	−0.10	−0.02	0.36	−0.81	0.62	−0.27	.788
	HAP-actual	**0.87**	**0.16**	**0.42**	**0.05**	**1.70**	**2.10**	**.037**
	LAP-actual	−0.62	−0.12	0.37	−1.36	0.12	−1.66	.099
	HAN-actual	**1.37**	**0.26**	**0.38**	**0.62**	**2.11**	**3.26**	**<.001**
Base-Ideal								
	Country (US-JP)	**1.97**	**0.50**	**0.53**	**0.94**	**3.01**	**3.75**	**<.001**
	Age	**−0.07**	**−0.23**	**0.02**	−0.12	**−0.03**	**−3.51**	**<.001**
	Gender (F–M)	0.31	0.08	0.50	−0.67	1.29	0.62	.536
	HAN-ideal	**1.53**	**0.20**	**0.46**	**0.63**	**2.44**	**3.34**	**<.001**
Ideal								
	Country (US-JP)	**1.86**	**0.47**	**0.59**	**0.69**	**3.03**	**3.15**	**.002**
	LAN-ideal	0.36	0.05	0.54	−0.70	1.43	0.67	.505
	HAP-ideal	0.05	0.01	0.37	−0.68	0.78	0.14	.888
	LAP-ideal	0.10	0.02	0.43	−0.76	0.95	0.22	.825
	HAN-ideal	1.24	0.17	0.65	−0.03	2.52	1.92	.056

Note. While covariates (age and gender) are included in all models, they are only reported here for the base model. Full results (including models for solace and distract regulation) are available in our OSF repository. Bold values indicate statistical significance, $p < .05$. CI = confidence interval; *LL* = lower limit; *UL* = upper limit; F= female; M =male; HAN = high-arousal negative; HAP = high-arousal positive; LAN = low-arousal negative; LAP = low-arousal positive; US-JP = United States–Japan.

through music (solace and distraction regulation: see OSF repository), we noticed that discharge regulation was the only regulatory style where culture exerted a significant effect, and that discharge regulation was also most strongly associated with HAN emotional experiences (no significant effect was observed for distract regulation, and a considerably smaller effect was observed for solace regulation). As music preferences emerge from these individual tendencies, this may explain the cultural-level effects observed in music consumption and NE in Study 4 (Table 6).

General Discussion

Overall, these studies show that cultures differ in preferences for music, and that the danceability of a culture's Top 50 songs reflects the amount of negative affect experienced by a culture, by potentially representing the usage of discharge regulatory strategies of music listening.

Musical Features as Representations of Culture

We highlight the usefulness of cultural product analyses for bottom-up, cross-cultural research. Like other cultural products, music (features) provides a more objective measure of population behavior with less interference from survey and response biases (see Kemmelmeier, 2016). With the advancement of big data and computing technologies, the process for obtaining such physical representations of culture has become simpler and faster. Music offers an advantage in that it is closely linked to human affect (see Dunbar, 2012), yet offers features that are almost universally perceived and understood. Beginning with bottom-up methods (Studies 1 and 2), we were ultimately able to infer culturally based explanations and develop hypotheses for the relationship between cultural preferences for emotion and music based on danceability (Studies 3–5). Through this process, we demonstrate the usefulness of music features, specifically danceability, in representing sociocultural norms and values.

Danceability and Affect Regulation

For the individual, discharge regulation appears linked to subjective experiences of HAN emotions in daily life. Given that danceability may signify the arousal levels of a song, we posit that danceability likely indicates the overall prevalence of discharge regulatory strategies of music listening from a culture. Here, we discuss this theory in terms of its arousal and valence components. For arousal, our findings showed that loose cultures have greater cultural affordances for high-arousal emotions: Study 4 showed that cultures with more loose norms have more prevalent experiences of high-arousal emotion. Dance itself is often a high-arousal activity, and (looser) regions, where dancing is commonplace may also prefer more danceable music. Accordingly, we found consistent results in Study 3, where dance functions of music listening were higher in the United States (loose) than Singapore (tight), and significantly associated with independent self-construal.

Yet, in the same study, danceable music did not appear to be a strategy used by independently oriented participants or U.S. participants to upregulate HAP emotions. In considering valence, we

Table 6
A Summary of the Aims, Methods, and Main Findings of Each Study

Study	Aims	Method	Main finding
1	Exploratory—classify Japanese/U.S. Songs and explore features behind the model	GBDT classifier on Spotify data (as cultural products)	High classification accuracy (i.e., strong differences), and danceability and instrumentalness as strong, interpretable predictors (features)
2	Exploratory—confirm cultural differences in identified features	Comparison of East-West Top 50 Charts	Danceability was significantly different between East Asian and Western music charts
3	Confirmatory–cultural differences in arousal preferences in human participants	Survey on music preferences of Singaporeans and Americans	Compared to Singaporeans, U.S. participants preferred high-arousal music. However, independent orientation predicted arousal preferences in both passive and recreational contexts.
4	Confirmatory–cultural differences in danceability and NE experiences	60-country mixed effects modeling of country-level emotion experience and Top 50 Spotify danceability	Negative emotion experience (frequency) and tightness–looseness significantly predicted Top 50 danceability scores. We theorize an explanation through danceability in music facilitating cross-cultural tendencies toward discharge regulation of negative affect
5	Confirmatory–cultural differences in discharge regulation can be attributed to differences in HAN emotions	Survey on affect valuation and experience with discharge regulation in United States and Japan	We show a link between negative affect, particularly HAN, culture, and discharge regulation: greater HAN prevalence is linked to increased discharge regulation in participants, and is stronger in United States than Japan.

Note. GBDT = gradient boosted decision tree; NE = negative emotion; HAN = high-arousal negative.

noted a stronger effect of NE representation across Studies 3–5. As mentioned earlier, Study 3 showed no effect on HAP emotion upregulation. Study 4 showed a much weaker and inconsistent result of danceability with PE experience across cultures, compared to a clear and consistent relationship between NE experience and danceability. Finally, Study 5 showed that the hypothesized mechanism of discharge regulation in accounting for earlier effects, was stronger and clearer in both ideal and actual (experienced) HAN emotions, than ideal and actual (experienced) HAP emotions. In sum, these studies converge to show that danceability differs across cultures, in reflecting the societal prevalence of NEs, by indicating the extent of discharge regulatory strategies of music listening within that society.

This has implications for cross-cultural psychological research, in presenting a new avenue for quantitative estimation of cultural differences in emotion regulation, that combines the benefits of computerized music information retrieval (e.g., reduced response bias) for cultural emotion-index computations. As music is a product of culture, automated danceability computations can be applied to estimate the emotion regulation tendencies in subcultures or regions, especially if combined with other psychosocial indicators (e.g., Gallup poll data, Google Trends). Additionally, we think that danceability can also be used to track emotion regulation styles over time. Given the availability of historical chart records and digitalized music data, this approach may be useful for historical research into emotional trends and patterns (see Muthukrishna et al., 2021), that would be inaccessible with traditional (self-report) methods of emotion assessment.

Differences in Music Produced Versus Consumed

Our article also examines differences in music produced and consumed by a culture, in combining two approaches often used in cultural products research. The music produced by a culture represents the cumulative esthetics of the individual members within it: music created by an artist embodies their esthetics and influences, and analyzing the aggregated "esthetics" of artists within a culture may reveal traits and tendencies pertinent to members of that culture. At the same time, music consumption (e.g., Spotify charts) reflects the cumulative preferences of a society, and is susceptible to external influences. For example, research has shown that familiarity affects popularity (North & Hargreaves, 1995), so repeated playbacks of music in commercials or entertainment programs may lead to that music making the charts. Although, advertisers targeting a specific culture may choose music belonging to styles that are popular within that culture. Ranking metrics may also function as gatekeepers, in that music that is considerably different from popular styles would still not become popular. Music consumption may also be limited by production; the accessibility of music within a specific cultural group. In Study 4, we mentioned that low-SES groups may face difficulties with accessing music from different cultures, and the music consumed may then from greater exposure to music produced by the local society. Therefore, we conducted Studies 1 and 2 that adopted these two different approaches, and found converging results: danceability was identified as a feature that differed across cultures in both music produced (Study 1) and consumed (Study 2), suggesting that cultural preferences for danceability in music were generalizable despite these constraints.

Limitations

Given the close replications between Spotify's danceability and Essentia's CNN danceability in Study 4 (but not with Essentia's DFA danceability), this suggests that the type of danceability used in this study may be closer to modeled human annotations (subjective evaluations) of music that suitably facilitates dance, and not so much an acoustic (DFA), low-level measure of danceability. On one hand, this could be problematic, as cultural biases (such as the annotators' cultural background) may have influenced these notions of danceability. On the other hand, these subjective perceptions may still be more accurate in representing a universal notion of danceability than the low-level DFA. Secondly, recent research has even emerged to show that cultural differences in rhythmic feature recognition and perception may exist (Jacoby et al., 2021), and this may potentially bias definitions of danceability toward a more Western conceptualization of danceability. Nevertheless, research has also argued for a certain universality in rhythmic perception, as most consumers of music around the world (at least those that have access to Spotify), may have been exposed to some form of Western music traditions (such as 12-tone equal-tempered scales). Furthermore, it is unlikely that music traditions (that afford perceptual differences) would evolve independently of cultural traditions (see culture-music coevolution; Savage et al., 2021), so the structural and institutional differences that shape society may also inadvertently shape both music preference and perception simultaneously. A longitudinal or experimental study would help unravel mechanisms used as such, while clarifying some of the identified confounds (e.g., income inequality) in influencing individuals' preferences for danceable music.

Next, we did not account for measurement invariance in the scales used across cultural groups for survey-based studies (Studies 3 and 5). While this was less of an issue for Study 5, we note that the scales used in Study 3 showed poor invariance across groups (Singapore and the United States). Results from measurement invariance tests and reliability for these scales are available as Markdown files in our OSF repository.

Finally, our research does not examine dance as an activity. This limited the conclusions that were made on culture and emotion expression and regulation: Does the society need to be approving of dance itself for danceable music to effectively downregulate HAN emotions, or can effective downregulation happen through a music-processing mechanism (such as rhythmic entrainment: Trost et al., 2017) independent of the cultural context?

Conclusion

We started out with exploratory analyses to examine how music features could represent cultural differences in emotion, and identified danceability and its usefulness in indicating the cultural affordances for HAN emotions in a society by quantifying the use of discharge regulation strategies in music. Our research shows that the frequency of experience of HAN emotions in a culture's preferred music can be reliably predicted by danceability in music, and that HAN emotional experiences are associated with discharge regulation. Going beyond danceability, we also show the usefulness of examining digital trace data, such as music features on Spotify's database, as a convenient, robust, and powerful method to quantify differences in psychological tendencies (and emotions) around the world.

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