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

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All online supplementary material is located in our OSF 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 is available online.

Data is also available upon request to the corresponding author.

Abstract

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. The exploratory section (Studies 1 and 2) identified differences in music preferences through machine learning of East-Asian and Western popular music on Spotify (combined $N = 1006644$). 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 $N_{\text{songs}} = 3343$, $N_{\text{participants}} = 495$, $N_{\text{countries}} = 60$) 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, or listening to music to cathartically release HAN emotions, would then skew music preferences towards 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 towards affective (HAN emotion) norms beyond commonly-used self-report paradigms. (235 words)

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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* (Stevens & Byron, 2016; Fritz et al., 2009; Purves, 2017; Cowen et al., 2020). 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 paper, we explore cultural differences in music preferences as a reflection of wider socio-cultural 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 behaviour, 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 aesthetics (e.g., analytic versus holistic attention styles, Wang et al., 2010). These ‘cultural’ products are public, tangible, and shared, reflecting the intersubjective consensus of a given culture (Morling & Lamoreaux, 2008; Lamoreaux & Morling, 2012). 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 behaviour. 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, Twitter posts, and children's books) due to 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, Thompson, & Matsunaga, 2004). For example, music with strong rhythmic and percussive features are 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 lower-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 higher arousal positive (HAP) emotions (e.g., excitement, elation), and East Asians prefer lower arousal positive (LAP) emotions (e.g., calm, serenity), and extends to preferred arousal levels in music. Tsai and colleagues (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 high arousal positive and negative 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, Mesquita, & Karasawa, 2006) that are usually high-arousal (Lim, 2016). By contrast, collectivistic, interdependent societies may prioritise social harmony, thereby favoring socially engaging emotion 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 higher arousal music preferences. However, to 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 down-regulation of 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, 2008; 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., 2020). We propose that elucidating these mechanisms could aid our understanding of music preference as a reflection of socio-cultural 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 paper, 5 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) aesthetics 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: Study 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 US (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 = 1006644 songs) based on a final list of artists (Japan = 2515; US = 1834) obtained from Spotify's recommendation systems on initial Top-50 playlists. We classified songs as produced by Japanese or Western¹ artists based on all 13 features from Spotify's Application Package 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 US-Japan differences in terms of affect.

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 a number of 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.

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

Loudness	The overall intensity of the song in decibels (dBFS).
Speechiness	A confidence measure on the presence of spoken words (e.g., audio books) in a song.
Valence	An estimate of whether a song conveys positive or negative affect.
Tempo	The estimated of the main tempo of a song.

Table 1: A list of song-level audio features obtained from Spotify

(<https://developer.spotify.com/documentation/web-api/reference/tracks/get-audio-features/>)

Methods and Analysis. Study 1 was conducted on Spotify data using the Spotifyr (Thompson, Parry, & Wolff, 2019) wrapper for the Spotify API, and a total of $N = 503322$ Japanese songs and $N = 678218$ Western songs (later down-sampled to $N = 503322$ songs for balanced comparison) were collected. This was based on a list of artists (Japan = 2515; Western = 1834), determined via a pseudo-snowball sampling strategy: where Spotify’s recommendation systems on initial Top-50 playlists from Japan and the US were repeatedly used for up to 3 iterations (2 for the US), 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 re-releases or compilation albums) were removed based on Spotify track ID. A list of artists, genres, and songs, and release years are available on our OSF repository. Japanese songs were obtained in July 2020, and Western songs was obtained in November 2019.

For each song, a list of scores for various musical features were 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 higher-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 generalisability 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 centred and standardised. 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 within the predictor variables.

GBDT refers to a decision-tree based ensemble method for machine learning that utilises sequential iterations of multiple decision trees. In this method, successive trees are fitted to minimise the residuals, resulting in a model that is often capable of high-accuracy predictive learning. For more information on GBDTs, see Friedman (2001). To minimise the risk of overfitting while training the model, we used 5-fold 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 (R Core Team, 2017), using the ‘caret’ wrapper (Kuhn, 2008) for the ‘gbm’ package (Greenwell et al., 2019). The analysis scripts are also available on our OSF repository.

Results and Discussion. The model achieved a moderate accuracy (0.76, 95%CI [0.75,0.76], Area Under the Curve [AUC] = 0.83), above a no information rate (NIR) 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 relative variable importance (RVI) of each predictor in the model (see our OSF repository). 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 towards 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 partial dependence plots (PDPs) in Figure 1. PDPs visualise 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.

Figure 1: Partial Dependence Plots (PDP) indicate the relationship between each music feature and culture, in computing the unidirectional classification probability of songs as Japanese (1) or Western/US (0) across the range for the target feature, with all other features held constant. The bottom left panel, for example, shows that higher danceability was more predictive of a song being Western than Japanese.

Our goal was to identify features that could potentially indicate cultural affordances for affect from the RVI list that could explain the US-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 collection of low-level features that quantify 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, such as most classical music, often has a calming, relaxing effect on the listener, reducing negative emotions (such as anxiety and stress; Labbé et al., 2007) through solace or distract regulation strategies (Saarikallio, 2008). This would be consistent with AVT, in that East Asians prefer LAP emotions. Energy, which encompasses a variety of different lower-level features like spectral density, intensity, and entropy, can also be seen as linked to arousal, but was excluded from further analysis due to the vagueness in Spotify documentation and difficulties with defining it. 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, these differences may also arise due to platform or sample biases. 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 generalised Western (US, UK, 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 products research (e.g., Pérez-Verdejo et al., 2020) as they function as selection processes that capture the prevalent musical preferences of a culture. Following Study 1's results, we hypothesised 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.

Methods and Material. Songs were obtained from the Spotify Top-50 Playlists (charts) for 4 East-Asian (EA) cultures (Japan, Taiwan, Hong Kong, Singapore) and 4 Anglo-Western (AW) cultures (US, UK, Canada, Australia). Data was obtained at two time-points 5 months apart (December 2018 and April 2019) for a total $N(\text{songs}) = 800$. All data was obtained through the SpotifyR package in R. All material (dataset and Jamovi analysis files) are available on our OSF repository. Pairwise comparisons were conducted using Student's t testing for danceability, and Mann-Whitney U testing for instrumentality, 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, instrumentality was inconsistent as it significantly differed between cultures in the opposite direction from Study 1: instrumentality was significantly higher in Western than in East Asian charts ($U = 71629$, $95\%CI [-0.00005, -0.00003]$, $p < .001$, $d = -0.17$). 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 to affect-based affordances. Danceability measures the rhythmic salience of a song, which tends to be

universally perceived as high-arousal and associated with dance activities (Savage et al., 2015; Mehr et al., 2019). 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) undergraduates². 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: 1) preferences for (positive and negatively-valenced) high arousal music should be stronger in the US than Singapore. 2) Individuals in the US 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 culture effects through self-construal at the individual level. Given that the US is typically more

² 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.

independently oriented than East Asia (incl. Singapore) (Markus & Kitayama, 1991), we posit that, 3) 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 (Sloboda & O'Neill, 2001; Krause & North, 2014). 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 rated the arousal for these playlists, and provided information on musical reward styles and cultural self-construal. However, as reported in the results section below, 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 was administered to 268 participants (Singapore: N = 127, $M_{\text{age}} = 21.4$, $SD = 1.8$, Females = 93, Males = 34; US: 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 (University 1) and the US (University 2: anonymised for review) for course credit. Participants from Singapore completed the web-based questionnaire on their own time, participants from the US 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 which, 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 purposes of our study, we assumed the Arousing factor to reflect high-arousal preferences³. 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 (high-arousal positive 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, 1997), 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 TOST equivalence test 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'

³ 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.

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 ANOVAs were conducted to examine cultural differences for arousal, music reward, and independence/interdependence. A significant difference was found for Arousing, $F(1, 236) = 5.53, p = .019$, and Sensory Motor, $F(1, 266) = 20.6, p < .001$, with post-hoc tests revealing significant differences (Tukey HSD) for Sensory Motor ($t(266) = -4.53, p < .001$), and Arousing ($t(266) = -2.35, p = .019$). *US* participants preferred dance functions of music more than Singaporean participants, and they also preferred more arousing music. No other significant differences were observed. This supports our first hypothesis that US 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 ($b = 0.09, SE = 0.05, 95\%CI [0.001, 0.18], t = 2.00, p = 0.047$), Social Reward ($b = 0.03, SE = 0.02, 95\%CI [0.003, 0.07], t = 2.14, p = 0.033$), Sensory Motor ($b = 0.07, SE = 0.02, 95\%CI [0.04, 0.11], t = 4.08, p < .001$), Musical Seeking ($b = 0.03, SE = 0.02, 95\%CI [0.001, 0.06], t = 2.06, p = .041$), and Mood Regulation ($b = 0.03, SE = 0.01, 95\%CI [0.003, 0.06], t = 2.21, p = 0.028$). 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 US than Singapore, nor higher in independently-oriented (than interdependently-oriented) individuals, suggesting that musical HAP up-regulation 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 US, which suggest 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 US 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. 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:

1) Elucidate relationships 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 generalise 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).

2) Modelling 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. Societies with lower socioeconomic statuses have generally narrower music preferences (Chan & Goldthorpe, 2006). One possibility could be through limited 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 towards dance music, these could spread within their spheres of political or cultural influence, e.g., 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, 3) 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 dataset. 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 (as of 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 per capita, negative emotion experience, and individualism. Scores for individualism were obtained from Hofstede's Cultural Insights (Hofstede, Hofstede, & Minkov, 2010), and negative/positive emotion experience, and GDP were obtained from the World Happiness Report 2019 (Helliwell, Layard, & Sachs, 2019). Negative emotion experience scores were the sample prevalence of the presence of negative emotion experiences (averaged score of anger, worry, and sadness) experienced by participants in the preceding day. This was similar for 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) dataset (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 dataset (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 catalogue, 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 is publicly accessible in our OSF repository.

Results

Affect, Individualism and Tightness

Spotify Danceability. We first 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 Satterthwaith's method in jamovi (the jamovi project, 2020). Note that, as the number of countries included in each regression analysis differed according to the dataset 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 dataset. For affect, we fitted a model predicting Spotify's danceability at the song-level, and country-level predictors of positive and negative emotion experience (PE and NE), 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 ($b = 0.41$, $SE = 0.10$, 95% CI [0.21,0.60], $t(57.1) = 4.10$, $p < .001$), but not PE ($b = 0.13$, $SE = 0.07$, 95% CI [-0.002,0.26], $t(57.0) = 1.93$, $p = .058$) or GDP per capita ($b = -0.02$, $SE = 0.01$, 95% CI [-0.04,0.0008], $t(56.8) = -1.88$, $p = .066$). We then fitted a second model 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 ($b = 0.41$, $SE = 0.10$, 95% CI [0.23,0.60], $t(57.1) = 4.10$, $p < .001$), but not individualism ($b = -0.0005$, $SE = 0.0003$, 95% CI [-0.001,0.0001], $t(54.8) = -1.45$, $p = .154$), PE ($b = 0.12$, $SE = 0.07$, 95% CI [-0.006,0.25], $t(54.9) = 1.86$, $p = .067$), or GDP per capita ($b = -0.008$, $SE = 0.01$, 95% CI [-0.03,0.02], $t(54.8) = -0.66$, $p = .512$).

We then fitted a separate model using country-level scores for tightness-looseness (Uz, 2014), that also reflect independence-interdependent social norms, and corresponding emotional expression for positive and negative emotions (Liu et al., 2018). NE, PE, and GDP per capita were also included as covariates. Using Uz's (2014) domain-general estimations of tightness-looseness from $N = 34$ countries that had Spotify data available (from our dataset), a REML model ($R^2_{\text{Marginal}} = 0.064$, $R^2_{\text{Conditional}} = 0.117$) showed a significant effect of tightness-looseness ($b = 0.001$, $SE = 0.003$, 95% CI [0.0005,0.002], $t(28.9) = 4.10$, $p < .001$), and NE ($b = 0.26$, $SE = 0.11$, 95% CI [0.05,0.48], $t(29.1) = 2.42$, $p = .022$). No significant effects were observed for PE ($b = 0.04$, $SE = 0.07$, 95% CI [-0.10,0.17], $t(29.1) = 0.56$, $p = .581$), and GDP per capita ($b = -0.02$, $SE = 0.01$, 95% CI [-0.04,0.01], $t(29.0) = -1.15$, $p = .260$).

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 ($N = 61$ countries; $R^2_{\text{Marginal}} = 0.122$, $R^2_{\text{Conditional}} = 0.264$) revealed a significant effect of NE ($b = 0.39$, $SE = 0.14$, 95% CI [0.11,0.67], $t(56.9) = 2.75$, $p = .008$), PE ($b = 0.27$, $SE = 0.09$, 95% CI [0.09,0.46], $t(56.9) = 2.93$, $p = .005$), and GDP per capita ($b = -0.04$, $SE = 0.01$, 95% CI [-0.07,-0.01], $t(56.8) = -2.94$, $p = .005$). However, with the inclusion of tightness-looseness, no significant effects were found ($N = 34$ countries; $R^2_{\text{Marginal}} = 0.037$, $R^2_{\text{Conditional}} = 0.174$) for tightness-looseness ($b = 0.0006$, $SE = 0.0004$, 95% CI [-0.0001,0.001], $t(28.9) = 1.49$, $p = .147$), NE ($b = 0.25$, $SE = 0.17$, 95% CI [-0.08,0.58], $t(29.0) = 1.47$, $p = .152$), PE ($b = 0.13$, $SE = 0.11$, 95% CI [-0.08,0.34], $t(29.0) = 1.12$, $p = .244$), and GDP per capita ($b = -0.01$, $SE = 0.02$, 95% CI [-0.06,0.03], $t(29.0) = -0.69$, $p = .493$).

For CNN danceability, the affect (NE, PE and GDP per capita) model ($N = 61$ countries; $R^2_{\text{Marginal}} = 0.078$, $R^2_{\text{Conditional}} = 0.203$) revealed a significant effect of NE ($b = 0.96$, $SE = 0.26$, 95% CI [0.44,1.47], $t(57.1) = 3.63$, $p < .001$), but not PE ($b = 0.33$, $SE = 0.17$, 95% CI [-0.01,0.67], $t(57.0) = 1.90$, $p = .063$), or GDP per capita ($b = -0.04$, $SE = 0.03$, 95% CI [-0.09,-0.01], $t(56.9) = -1.45$, $p = .151$). With the inclusion of tightness-looseness, ($N = 34$ 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 ($b = 0.003$, $SE = 0.0007$, 95% CI [0.003,0.004], $t(29.0) = 4.12$, $p < .001$), and NE ($b = 0.74$, $SE = 0.29$, 95% CI [0.17,1.31], $t(29.1) = 2.54$, $p = .017$). No significant effect was observed for PE ($b = 0.002$, $SE = 0.18$, 95% CI [-0.36,0.36], $t(29.1) = 0.01$, $p = .990$), and GDP per capita ($b = -0.01$, $SE = 0.04$, 95% CI [-0.08,0.06], $t(29.0) = -0.31$, $p = .761$).

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 localised effects in specific 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. The model ($N = 31$ countries; $R^2_{\text{Marginal}} = 0.09$, $R^2_{\text{Conditional}} = 0.116$) showed a significant effect of income inequality, through the GINI index ($b = 0.006$, $SE = 0.001$, 95% CI [0.003,0.008], $t(24.7) = 4.09$, $p < .001$), and

tightness-looseness ($b = 0.0009$, $SE = 0.0002$, 95% CI $[0.0004, 0.001]$, $t(24.8) = 3.44$, $p = .002$), but no significant effects were observed for NE ($b = 0.11$, $SE = 0.10$, 95% CI $[-0.07, 0.30]$, $t(24.9) = 1.18$, $p = .247$), PE ($b = 0.05$, $SE = 0.06$, 95% CI $[-0.06, 0.16]$, $t(25.0) = 0.911$, $p = .371$), and GDP per Capita ($b = 0.01$, $SE = 0.02$, 95% CI $[-0.01, 0.05]$, $t(24.9) = 1.05$, $p = .303$).

Using the DFA danceability measure, the model ($N = 31$, $R^2_{\text{Marginal}} = 0.078$, $R^2_{\text{Conditional}} = 0.180$) showed a significant effect of income inequality ($b = 0.007$, $SE = 0.002$, 95% CI $[0.002, 0.01]$, $t(24.9) = 2.65$, $p = .007$), but no significant effects were observed for NE ($b = 0.11$, $SE = 0.10$, 95% CI $[-0.07, 0.30]$, $t(24.9) = 1.18$, $p = .247$), PE ($b = 0.05$, $SE = 0.06$, 95% CI $[-0.06, 0.16]$, $t(25.0) = 0.911$, $p = .371$), tightness-looseness ($b = 0.0009$, $SE = 0.0002$, 95% CI $[0.0004, 0.001]$, $t(24.8) = 3.44$, $p = .002$), and GDP per Capita ($b = 0.01$, $SE = 0.02$, 95% CI $[-0.01, 0.05]$, $t(24.9) = 1.05$, $p = .303$). 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 ($b = 0.01$, $SE = 0.004$, 95% CI $[0.006, 0.02]$, $t(24.8) = 3.46$, $p = .002$), and tightness-looseness ($b = 0.002$, $SE = 0.0007$, 95% CI $[0.0009, 0.004]$, $t(24.9) = 3.25$, $p = .003$), but no significant effects were observed for NE ($b = 0.38$, $SE = 0.27$, 95% CI $[-0.16, 0.92]$, $t(25.0) = 1.39$, $p = .176$), PE ($b = 0.02$, $SE = 0.16$, 95% CI $[-0.29, 0.34]$, $t(25.0) = 0.151$, $p = .881$), and GDP per Capita ($b = 0.07$, $SE = 0.04$, 95% CI $[-0.02, 0.15]$, $t(25.0) = 1.525$, $p = .142$). In sum, countries with greater income inequality have 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. Furthermore, a statistical mediation analysis conducted with danceability aggregated at the country-level (DV), NE (IV), and income inequality (mediator), revealed a significant indirect

effect ($b = 0.28$, $SE = 0.09$, $95\%CI[0.11,0.46]$, $B = 0.32$, (Sobel's) $Z = 0.32$, $p = .001$. NE significantly predicted income inequality ($b = 57.8$, $SE = 13.7$, $95\%CI[30.9,84.8]$, $B = 0.53$, $Z = 4.21$, $p < .001$), which predicted danceability ($b = .005$, $SE = .001$, $95\%CI[0.003, 0.007]$. $B = 0.60$, $Z = 5.01$, $p < .001$). This suggests that the variance explained by NE in predicting danceability can also be explained by the GINI scores per country. Our interpretation is that countries with high income inequality would also have greater affordance for negative emotions (country-level; Pearson's $r = 0.53$, $95\% CI [0.28,0.71]$, $p < .001$), which can be reflected through greater consumption of danceable music.

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 aesthetics 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 ($b = 0.27$, $SE = 0.10$, $95\% CI [-0.07,0.47]$, $t(34.0) = 2.66$, $p = .012$). No significant effects of PE and GDP per culture were observed. As colonial history was deviation coded, we observed a significant effect of coloniser for Brazil ($b = 0.001$, $SE = 0.01$, $95\% CI [0.01,0.14]$, $t(34.1) = 2.35$, $p = .025$), Central America ($b = 0.09$, $SE = 0.02$, $95\% CI [0.05,0.13]$,

$t(33.8) = 4.16, p < .001$), Colombia ($b = 0.08$, $SE = 0.02$, 95% CI $[0.03, 0.12]$, $t(34.1) = 3.12, p = .004$), Czechoslovakia ($b = -0.07$, $SE = 0.02$, 95% CI $[-0.12, -0.03]$, $t(33.9) = -3.09, p = .004$), Haiti ($b = 0.08$, $SE = 0.03$, 95% CI $[0.02, 0.15]$, $t(34.1) = 2.72, p = .010$), Russia ($b = -0.04$, $SE = 0.01$, 95% CI $[-0.05, -0.005]$, $t(34.3) = 2.39, p = .040$), Spain ($b = 0.07$, $SE = 0.01$, 95% CI $[0.04, 0.10]$, $t(34.0) = 5.04, p < .001$), Sweden ($b = -0.11$, $SE = 0.03$, 95% CI $[-0.17, -0.05]$, $t(34.1) = -3.52, p = .001$), and the USA ($b = -0.08$, $SE = 0.03$, 95% CI $[-0.14, -0.008]$, $t(34.1) = -2.19, p = .035$). In sum, compared to the mean across all levels, Top 50 songs from countries that were historically colonised by Brazil, Central America, Colombia, Haiti, and Spain had higher danceability, and Top 50 songs from countries colonised by Czechoslovakia, Russia, Sweden, and the USA had lower danceability. Countries with no colonization history also had significantly lower danceability than the average ($b = -0.03$, $SE = 0.01$, 95% CI $[-0.05, -0.005]$, $t(34.3) = -2.39, p = .023$). Even after controlling for this effect, NE significantly predicted danceability. 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 ($b = 0.28$, $SE = 0.13$, 95% CI $[0.03, 0.54]$, $t(48.8) = 2.15, p = .037$). Full results are reported in the OSF repository.

Discussion

Our results showed a strong and stable effect of negative emotion experience (NE) 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 negative emotions on a cultural level, predicted the danceability of songs on their Top 50 charts.⁴ While association with negative emotions was not significant after the inclusion of income inequality, this may be still be consistent in that income inequal societies also have higher prevalence of negative emotions.

Danceability and High-Arousal Negative Affect

This is further contextualised 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.

⁴ 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).

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 negative emotion experience was drastically reduced. Past research has shown that low socioeconomic status (SES) creates the environment for increased negative emotions (Gallo & Matthews, 2003), and that income inequality is itself also associated with more negative emotions (Godoy et al., 2006). Accordingly, in our data, we found a similar correlation between negative emotion 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 high arousal negative (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 theorised 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 (Sherman & Dingle, 2015). Danceability could thus reflect the HAN emotion prevalence within a culture, by representing its cultural tendencies towards discharge listening in music to downregulate it. If 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 high arousal negative emotions may not need discharge regulation, but can make do with solace or distract regulation methods that are better suited to down-regulate low arousal negative states (Saarikallio, 2008).

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 US (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 US ($N = 111$, $M_{\text{age}} = 33.5$, $SD = 12.9$, Females = 52, Males = 53, Others = 4, Rather not say = 2), recruited from the *Lancers* (JP: <https://lancers.jp>) and *Prolific* (US: <https://prolific.co>) crowdsourcing platforms for ¥500 and \$10.00 respectively. Participants completed the Affect Valuation Index (AVI; Tsai, 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: high-arousal negative (HAN; e.g., fearful, hostile), high-arousal positive (HAP; e.g., enthusiastic, excited), low-arousal negative (LAN; dull, sluggish) and low-arousal positive (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 towards negative emotion downregulation. Participants provided demographic information, such as age, gender, music experience, SES, ethnicity, etc., and was approved by the respective Institutional Review Boards of University 1 and University 2 (anonymised for review) for data collection in the US 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 ($b = 1.5$, $SE = 0.31$, $95\%CI [0.91, 0.21]$, $t(219) = 4.93$, $p < .001$), where higher HAN-actual scores were associated with higher discharge regulation scores. Country was also significant in predicting discharge regulation (Japan as reference; $b = 1.80$, $SE = 0.51$, $95\%CI [0.78, 2.81]$, $t(219) = 3.53$, $p < .001$), where discharge regulation was stronger in the US 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 that HAN-actual was still predictive of discharge regulation ($b = 1.4$, $SE = 0.38$, $95\%CI [0.62, 2.11]$, $t(215) = 3.63$, $p < .001$), as with country ($b = 1.21$, $SE = 0.58$, $95\%CI [0.08, 2.34]$, $t(215) = 2.10$, $p = .037$), in similar directions. Furthermore, HAP-actual also significantly predicted discharge regulation ($b = 0.88$, $SE = 0.42$, $95\%CI [0.05, 1.70]$, $t(215) = 2.10$, $p = .037$), albeit to a smaller extent than HAN-actual.

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 ($b = 1.5$, $SE = 0.46$, $95\%CI [0.63, 2.44]$, $t(217) = 3.34$, $p < .001$). 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.

Finally, we examined a mediation model involving country, HAN-actual, and discharge regulation. Culture was dummy coded as Japan = 0, and US = 1. All standard errors and confidence intervals were calculated on 1000 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 ($b = b = 0.24$, $SE = 0.10$, $95\%CI [0.05, 0.43]$, $B = 0.15$, $Z = 2.43$, $p = .015$), and HAN-actual significantly predicted discharge regulation ($b = 1.53$, $SE = 0.31$, $95\%CI [0.91, 2.12]$, $B = 0.29$, $Z = 4.94$, $p < .001$), for a significant indirect effect of country and HAN-actual on discharge regulation ($b = 0.36$, $SE = 0.17$, $95\%CI [0.03, 0.69]$, $B = 0.05$, $Z = 2.13$, $p = .033$). This suggests a significant partial mediation effect of HAN-actual on the relationship between culture and discharge regulation. Participants in the US 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 on 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 US, a culture with looser social norms (tightness-looseness domain-general scores from Uz, 2014: 71.5) and higher income inequality than Japan (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 US 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 positive emotion experiences on music listening across cultures. Additionally, in comparing results with other regulatory styles for negative emotion downregulation 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 emerges

from these individual tendencies, this may explain the cultural level effects observed in music consumption and NE in Study 4.

General Discussion

Overall, these studies show that cultures differ in preferences for music, and that the danceability of a culture's Top50 songs reflect the amount of negative affect experienced by a culture, by potentially representing the usage of discharge regulatory strategies of music listening.

Study	Aims	Method	Main finding
1	Exploratory - Classify Japanese/US 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, US participants preferred high arousal music for passive listening and low arousal music for recreational listening, and dance. However, independent orientation predicted arousal preferences in both passive and recreational contexts.

4	Confirmatory – cultural differences in danceability and negative emotion experiences	61-country mixed effects modelling of country-level emotion experience and Top-50 Spotify danceability	Negative emotion experience (frequency) and tightness-looseness significantly predicted Top-50 danceability scores. We theorise an explanation through danceability in music facilitating cross-cultural tendencies towards 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 US 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 US than Japan.

Table 3: A summary of the aims, methods, and main findings of each study.

Musical features as representations of culture

We highlight the usefulness of cultural products analyses for bottom-up, cross-cultural research. Like other cultural products, music (features) provides a more objective measure of population behaviour with less interference from survey and response biases (see Kimmelmeier, 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 high-arousal negative 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 US (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 US participants to upregulate HAP emotions. In considering valence, we noted a stronger effect of negative emotion 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 positive emotion experience across cultures, compared to a clear and consistent relationship between negative emotion experience and danceability. Finally, Study 5 showed that the hypothesised 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 that danceability differs across cultures, in reflecting the

societal prevalence of negative emotions, 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 computerised MIR (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 sub-cultures 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 digitalised 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 paper 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 aesthetics of the individual members within it: music created by an artist embodies their aesthetics and influences, and analysing the aggregated ‘aesthetics’ 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 be limited to music produced by the local society. Furthermore, due to complicated copyright arrangements, Spotify listeners may not have equal access to the same music from around the world: a Japanese song may not be available for American listeners and vice-versa. 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 generalisable 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 modelled 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 lower-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 towards a more Western conceptualisation 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., 2020), so the structural and institutional differences that shape society may also inadvertently shape both music preference and perception simultaneously. We think that this is a ripe area for collaborative research with disciplines like ethnomusicology and MIR, in that understanding the emergence of musical preferences may afford insight into the cultural traits and norms behind it.

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 (emotion) around the world.

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