Energy, popularity, and the circumplex: A computerized analysis of emotion in 143,353 musical pieces

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Abstract

The circumplex model of affect claims that emotions can be understood in terms of their relative positions along two dimensions, namely pleasant-unpleasant and active-sleepy; and numerous studies of small samples of music have yielded data consistent with this. The present research tests whether the energy and beats per minute of music (proxies for the arousal dimension) and popularity as expressed in terms of sale charts (a possible proxy for the pleasantness dimension) could predict scores on six moods in 143,353 pieces. Findings concerning energy were clearly consistent with the circumplex model; findings for beats per minute were consistent though more equivocal; and findings concerning popularity yielded only limited support. There were also numerous relationships between popularity and mood, indicative of the commercial market for music in specific genres; and there was evidence of considerable differences in the mood scores between genres. In addition to the circumplex model and aesthetic responses to music, the findings also have implications for music marketing, therapy, and everyday listening.

Key words: Music, emotion, circumplex, popularity, sales

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Many attempts to understand emotion in music have considered the degree of activity in the latter. North and Hargreaves (2008) and Sloboda and Juslin (2001) review numerous attempts in which participants have been typically asked to assess target pieces in terms of concepts such as ‘arousal’, ‘orderliness’, ‘complexity’, or ‘energy’, and these assessments are then mapped onto assessments of the more fine-grained details of emotional responses to those pieces. While many of these attempts have been successful, their obvious limitation is that they have employed a relatively narrow range of musical stimuli, which are often composed specifically for the research in question and presented to undergraduate participants under laboratory conditions. In contrast, the present research attempts to determine whether the activity of commercially-successful pieces of music can predict their emotional connotations across 143,353 unique pieces, which in effect represent the entire corpus of music that has enjoyed any degree of commercial success in the United Kingdom.

Sloboda and Juslin (2001) outline three major psychological approaches to conceptualizing emotion, namely categorical, prototype, and dimensional. Dimensional theories organize emotions according to their relative position along a small number of dimensions. Perhaps the best-known of these is the circumplex model (Russell, 1978, 1980). This states that any emotion can be characterized according to its location along two orthogonal dimensions, namely pleasant-unpleasant and arousing-sleepy. For example, ‘tension’ can be characterized as a combination of high arousal and unpleasantness, whereas ‘serenity’ can be characterized as a combination of sleepy and pleasantness. Any specific emotion can be conceptualized in terms of a particular quantity of pleasantness and arousal, so, for example, ‘aggressiveness’ represents a greater amount of arousal than does ‘strength’, and ‘elation’ represents a greater degree of pleasantness than does ‘thankful’.

This approach has been used successfully to study emotion in a variety of domains in recent years, including responses to climate change (Leviston et al., 2014); age differences in temporal variation in emotional state (English and Carstensen, 2014); affective social behavior (Carney and Colvin, 2010); facial expression of emotion (Tseng et al., 2014); and use of music in sports-related motivation (Loizou et al., 2014). Moreover, Posner et al. (2009) provide fMRI data detailing the neurophysiological bases of pleasantness and arousal in emotion.

Of greatest relevance to the present research, North and Hargraves (1997) found that ratings of pleasantness and arousal in response to 32 pieces of music could predict ratings of those same pieces in terms of eight different emotional responses: the results were consistent with the circumplex approach, such that pieces that were liked and arousing were also regarded as exciting, pieces that were disliked and not arousing were also regarded as boring, pieces that were liked and not arousing were regarded as relaxing, and pieces that were disliked and arousing were regarded as aggressive. Subsequent research on emotion in music has produced similar findings. Kreutz et al. (2008) found that pleasantness and activation ratings of music were related to the specific emotions it elicited; Ritossa and Rickard (2004, see also Madsen, 1998) showed that the emotions expressed by pieces of music could be predicted by a combination of subjective reports of evoked arousal and pleasantness (and also familiarity); and Schubert (2004) identified a link between arousal evoked by music (particularly via loudness and tempo) and emotional responses.

Similarly, although the evidence is not entirely consistent (e.g., Panksepp and Bekkedal, 1997), other studies show that physiological states indicative of greater physiological arousal are associated with more powerful emotional responses to music (such as experiencing shivers down the spine), just as the circumplex predicts (see reviews byBartlett, 1996;Scherer and Zentner, 2001): both Khalfa et al. (2002) and Rickard (2004, see also McFarland, 1985) found that emotionally powerful music gave rise to greater increases in skin conductance than did less emotionally powerful music; Dibben (2004) found that participants who had just exercised reported more intense emotional experiences of music than did participants who had relaxed; and Nyklicek et al. (1997) were able to identify reliable cardio-respiratory responses to different musically-induced emotions that were "related to the arousal dimension of self-reported emotions" (p. 304).

However, Kreutz et al. (2008) and several others have noted that the great majority of research to date has employed lab-based (usually undergraduate) participants listening to relatively short excerpts drawn from small samples of music, which have often been composed or performed specifically for the research. Although there has been some research in music information retrieval that has begun to consider emotion—for example, by overtly considering its role in recommendation systems (e.g., Eerola, et al., 2009; Qin, et al., 2014; Scirea, et al., 2015) and by specifically considering mood tags (e.g., Laurier, et al., 2009; Saari and Eerola, 2013; Saari, et al., 2013). This work has not considered emotion at the population level; and there are similarly exemplars of other research that has used models of emotion that are arguably less-widely employed than the circumplex (such as categorical models (e.g., using Hevner's (1936) adjective circle) and domain specific models (e.g., the Geneva Emotional Music Scales (GEMS) measure) – see Zentner & Eerola, 2010; Zentner, et al., 2008). Given the scale of interest in the circumplex approach as a means of explaining emotion in music, and the apparently supportive results among more limited samples of music and participants, there is a clear need to determine whether it can be corroborated in population-wide data that arguably reflects the totality of listening experience. Therefore, in order to carry out such a test, the present research employed a database containing all those pieces that had appeared on one of the UK sales music charts at any point: they represent a complete commercial musical culture.

The literature suggests two hypotheses concerning the relationships between the mood of music and its energy and tempo (representing the arousal-sleepy component of the circumplex), and its popularity (since this is arguably a population-wide proxy for the pleasantness dimension of the circumplex, although we return to this point shortly). Hypothesis 1 was that we might expect that energy and BPM would both be associated positively with the pieces expressing the emotions regarded by the circumplex approach as representing high levels of arousal, and negatively with those emotions regarded by the circumplex as towards the sleepy end of the dimension. We were more confident of results satisfying this hypothesis in the case of energy than in the case of BPM, as the former represents a more holistic assessment of the arousal intrinsic to a piece than does BPM (since tempo is only one of several possible factors that contributes to the activity of a piece (Berlyne, 1971)). The second hypothesis was that we might expect that hit popularity would be associated positively with the pieces expressing emotions that are positively-valenced. We have less confidence in this second hypothesis, however, as there are grounds to suspect that a measure of sales and popularity may not represent a direct test of the pleasantness dimension of the circumplex, and we return to this point in the Discussion. Nonetheless, data on sales and popularity allows us to also test related questions.

In particular, the research was also able to assess two related subsidiary issue on an exploratory basis, namely whether certain musical genres are more likely to evoke certain emotions rather than others. First, it allows us to test simply whether music that evokes certain moods enjoys greater popularity than does music that evokes other moods. Second, there is a long tradition within music psychology and musicology of attempting to identify certain emotional connotations as a reliable outcome of certain structural musical properties. Perhaps the best-known of these is still Cooke's (1959; see also Kaminska & Woolf, 2000) theory, which claims that certain melodic patterns have a directly communicative, almost linguistic, property in reliably communicating certain emotions, such that for example descending passages to the tonic are analogous to peace or rest, whereas passages moving away from the tonic are analogous to outgoing emotions. Indeed, Bruner (1990; see also Gabrielsson and Juslin, 1996;Juslin, 2000;Juslin and Laukka, 2000;Gabrielsson and Lindström, 2001;Juslin and Laukka, 2003;Juslin, 2005) reviewed numerous studies from the fields of psychology, musicology, and marketing, and summarized the various possible iconic meanings that different musical structures may have in terms of time-, pitch-, and texture-related factors. Similarly, Straehley and Loebach (2014) found that the emotional connotations of various musical modes could be captured in terms of their valence and intensity, consistent with the circumplex dimensions of pleasantness and arousal respectively. As such, we might expect the musical conventions of differing genres to lead to these genres having significantly different emotional connotations. Confirmation of such would have implications for several specific lines of research. North and Hargreaves (2008) review a number of studies within the public health and criminology literature on how certain musical genres, particularly rap and heavy metal (but also blues, country, and opera - see Stack and Gundlach, 1992;Stack, 2000; 2002), are often associated with negatively-valenced emotional responses, and these in turn have been claimed to be the cause of elevated mental health problems and juvenile offending among these individuals. Similarly, research on music therapy has identified significant effects (and notable effect sizes) of musically-induced emotion on a range of health-related outcomes, such as the experience of pain (see review by Standley, 1995). Consumer research has shown that using music to induce certain moods among customers can influence their purchasing (e.g., North et al., 2003); and research on everyday music listening has identified that one implication of the digitization and portability of music is that listeners place great value on their ability to control the music they experience, and seek to use certain genres to evoke desired emotional responses that are useful in the given context of music listening (Krause et al., 2014a). A more wide-ranging understanding of the relationship between genre and mood, based on the large data set employed here, could inform all these fields.

Method

Dataset

The research employed an adapted version of a master dataset used extensively within the music industry, with the adaptation created in partnership with a private sector organization. The master database contains information on over 38 million pieces of recorded music, which in effect represents all music recordings ever released on a commercial basis in Europe, North America, and Australasia since the beginning of the 20th century (including recordings of pieces composed before this date). The master database is compiled by a company, which aggregates information globally from over 400,000 record labels. The master database represents the canonical music catalogue used by radio stations, recording companies, and other media in music programming and other similar activities. On entry into the master dataset, the company concerned classifies each piece into one of 23 genres (namely, alternative/indie, blues, cast recordings/cabaret, children's, Christian/gospel, classical/opera, comedy/spoken word, country, electronica/dance, folk, instrumental, jazz, Latin, new age, pop, rap/hip hop, reggae/ska, rock, seasonal, soul/R&B, soundtracks, vocal, and world) on the basis of the recording artist in question: the initial classification of an artist incorporates information provided by the recording company in question. Note that tracks classified as 'comedy/spoken word' were deleted from the present dataset because the great majority did not contain any music, and any music they contain is clearly not the focus of the remainder. Pieces were also deleted for minority genres, for which there were fewer than 100 exemplars that also had popularity data. Created on 30 March 2015, the subset of this master dataset used in the present research contained 143,353 pieces of music, which were selected as those for which data also existed concerning sales in the United Kingdom, such that the pieces employed were all and only those that had enjoyed any commercial success whatsoever in that country: they represent a complete commercial musical culture.

Energy. The energy value for each piece was calculated via an algorithmic process that produced a score for each in turn based on its specific features: this approach is preferable to assigning scores to individual tracks on the basis of meta-data, such as genre classification, as it directly addresses the characteristics of the piece in question. The first step was derivation of a set of training tracks, consisting of 100 exemplar 'calm' and 100 exemplar 'energetic' pieces, which were selected by a team comprising two students who were heavy music consumers, a musicologist, and an audio engineer working collaboratively. This set of training tracks was used in order to train an AI process about the sonic differences between energetic and calm tracks using mathematical vectors based on the transformations of 11 sound properties (e.g., tempo, beat, pitch, and rhythm). For these tracks, the computer compared each individual track against the remaining 99 using an AI algorithm: if in the 10 most acoustically-similar tracks (again defined according to 11 computer-analyzed sound properties such as tempo, beat, pitch, and rhythm) there was a majority from the same proposed class as the seed track (i.e., calm versus energetic) then the target piece was regarded as having been classified appropriately. The initial batch of tracks yielded a successful classification rate of 92%, and the 18 incorrectly classified tracks were then replaced by others in subsequent iterations of the same process until all 200 of the seed tracks could be regarded as classified appropriately by this process. The trained AI process, referred to as an 'energy classifier', was then used to process every track in the database in terms of the 11 sound properties, and assign an energy value to each on the basis of the degree of similarity between its own values on the 11 sound properties and the values of the seed tracks. A similarity engine combined scores on 69 differing combinations of the 11 sound properties to determine the degree of similarity between a given piece and the other pieces in the database: this was accomplished by examining the degree of similarity on the values for each of the 69 combinations for each track in turn relative to the remainder of the tracks in the database. Each track was then assigned an energy value based on the similarity values so that the greater the similarity between two tracks so the greater the similarity in their energy scores: high values indicate an energetic track while low values indicate a calm track. The research team also carried out an informal human-listening test of 1000 tracks from the entire database, selected via a quasi-random process, which involved checking the face validity of relatively low, moderate, and high energy values produced by the AI system.

Beats per minute (BPM). Initially, we tested five different algorithmic measures of BPM for each of the genres employed in the present research. These candidate algorithms were based on the industry-standard open source C++ library developed by the Music Technology Group of Pompeu Fabra University (http://essentia.upf.edu). The outputs of each algorithm were then compared against human ratings of a sub-sample of tracks from each of the genres. The two algorithms that produced outputs with the highest correlation with the human ratings were then combined and subsequently employed in the present research. The BPM value for each piece was determined via computerized measurements that were taken for each successive 30-second segment of each track to allow for *rallentando* and other forms of tempo variation within the track. The tempo values for each segment were subsequently averaged to provide a single BPM value per piece. Once values had been calculated for each track, the same informal human listening test as described under the 'Energy' sub-heading indicated that the outputs of this process have good face validity, as they provide a good overall assessment of tempo; and separate unpublished tests of the accuracy of the process (versus manual measurements of tempo) carried out prior to commencement of the current research also suggest that this approach performs well.

Hit popularity. Each piece was assigned a hit popularity score that utilized data from the United Kingdom charts at both regional and national level. The measures incorporated data from general charts as well as genre-specific and regional charts. Each chart was assigned a weighting based on the size of the region covered (e.g., a national chart was weighted heavier than a regional chart, with the extent of the difference depending on the size of the region in question); whether the chart addressed singles or albums (with singles charts weighted heavier albums charts, as they are a more direct reflection of the popularity of the specific track in question); and whether the chart was general versus genre- or region-specific (with the extent of the difference in weighting of specific genre charts depending on the popularity of the genre and size of the region in question). For example, the United Kingdom singles chart was assigned a weighting of 1; the corresponding albums charts were assigned a weighting of .500 (i.e., 1/2); the United Kingdom classical specialist albums chart was assigned a weighting of .167 (i.e., 1/6); the United Kingdom Asian singles chart was assigned a weighting of .143 (i.e., 1/7); and the Scottish albums chart was assigned a weighting of .125 (i.e., 1/8). For each track per chart, the popularity score was calculated as 1 divided by (peak chart position multiplied by chart weighting), so that higher scores indicate greater popularity.

Mood scores. Each track was assigned values for each of six moods, represented by numbered adjective clusters, namely mood 1 = clean, simple, relaxing, mood 2 = happy, hopeful, ambition, mood 3 = passion, romance, power, mood 4 = mystery, luxury, comfort, mood 5 = energetic, bold, outgoing, and mood 6 = calm, peace, tranquility, respectively. These moods were employed at the discretion of the music industry at the time the initial database was devised, and are regarded by the industry as most relevant to radio programming (and similar commercial uses): nonetheless, they possess good face validity as 'typical' responses to music, and map well onto previous research on the circumplex, so that moods 1, 4, and 6 are located at the lower end of the arousal dimension whereas moods 2, 3, and 5 are located at the higher end of this dimension. Unfortunately, however, these moods do not reflect the negative end of the pleasantness dimension.

The mood scores were based on seed ratings of 300 pieces thought to represent a good range of all the moods concerned. Again, using human trained AI, six musicians and sound engineers provided ratings of how the music made them feel in order to create a training set of tracks for the AI process. The development of the mood scores involved a three-step machine learning process, similar to that for the 'Energy' score. First, an analysis module scored each piece according to audio descriptors based on melody, harmony, tempo, pitch, octave, beat, rhythm, noise, brilliance, and chord progression. Second, as per the energy score, a similarity engine combined scores on 69 differing combinations of the audio descriptors to determine the extent to which each track was similar to the others in the database. Third, each of the six mood scores for each piece were then determined on the basis of the mood scores assigned to similar tracks and the degree of similarity between those and the target piece on the 69 combinations of the audio descriptors. This allowed the computer to allocate percentage scores to each track that represented the extent to which it fitted each of the six moods. The same informal human listening test as described under the 'Energy' sub-heading indicated that the outputs of this process have good face validity.

Results

Energy, BPM, hit popularity, and mood

A series of General Linear Mixed Model (GLMM) analyses addressed the first and second hypotheses, namely whether energy, BPM, and hit popularity could predict scores on each of the six moods ($\alpha < .001$, to allow for the multiple analyses performed). Energy, BPM, and hit popularity served as predictor variables in six separate GLMM analyses concerning each of the mood scores in turn respectively. The effect sizes indicate that energy explained a much greater portion of the variance (ranging between 5-28%) than did BPM or hit popularity. This set of six analyses was then repeated for each genre separately ($\alpha < .001$). These analyses again indicated that energy predicted a greater portion of the variance in the mood scores than did BPM or hit popularity. These results are detailed in Tables 1a-f.

—Tables 1a-f —

Mood by genre

A second set of six GLMM analyses ($\alpha < .001$, to allow for the multiple analyses) considered variations between genres on each of the six mood scores respectively. All six analyses were significant (see Tables 2a-f), with the associated deviation contrasts demonstrating the scores for each genre relative to the overall mean score per mood. These results are detailed in Tables 2a-f.

—Tables 2a-f—

Discussion

Energy, BPM, hit popularity, and mood (Hypothesis 1)

Hypothesis 1 addressed the arousal dimension of the circumplex. Tables 1a-f show the relationship between each of energy, BPM, and hit popularity for each of the six moods in the case of both the overall dataset and for each genre in turn. Across the dataset as a whole, energy was related negatively to moods 1 (clean, simple, relaxing), 4 (mystery, luxury, comfort), and 6 (calm, peace, tranquility) and positively to moods 3 (passion, romance, power) and 5 (energetic, bold, outgoing). With very few exceptions, the same direction of (significant) findings was also identified for each of these moods in the case of each of the genres considered. On the whole, therefore, the results concerning energy appear consistent with the circumplex model. Findings concerning energy and mood 2 (happy, hopeful, ambition) were, however, more mixed: although the relationship was negative in the overall dataset, results concerning several of the individual genres indicated a positive relationship. One possible explanation of this is that Mano (1991) and Russell and Mehrabian (1977) have shown that the adjectives associated with mood 2 sit around the midway point of the activity dimension of the circumplex (although whether they are more prone to this issue than are the other moods investigated here is debatable).

As expected, the corresponding results concerning BPM yielded much weaker effect sizes, although many of the individual tests were nonetheless significant at the restricted alpha level, which is itself pleasing given that BPM is only one factor that contributes to the overall arousal of a piece. Across the dataset as a whole, BPM was related positively to mood 3 (passion, romance, power), and negatively to moods 4 (mystery, luxury, comfort) and 6 (calm, peace, tranquility), all of which is consistent with the circumplex model. Given the small effect sizes in the overall dataset, it is unsurprising, therefore, that only some of the individual genres yielded associations between BPM and the six mood scores, although again those that were significant were usually in the direction predicted by the circumplex model (although again subject to low effect sizes). There were negative relationships between mood 1 (clean, simple, relaxing) and BPM for jazz and pop, but also a positive relationship for electronica/dance. There were positive relationships between mood 2 (happy, hopeful, ambition) and BPM for country, jazz, and pop, but also a negative relationship for electronica/dance and rap/hip hop. There were positive relationships between mood 3 (passion, romance, power) and BPM for alternative/indie, country, jazz, pop, and rock. There were negative relationships between mood 4 (mystery, luxury, comfort) and BPM for alternative/indie, country, electronica/dance, pop, rap/hip hop, and rock. There were positive relationships between mood 5 (energetic, bold, outgoing) and BPM for jazz and pop, but also a negative relationship for electronica/dance. There were negative relationships between mood 6 (calm, peace, tranquility) and BPM for alternative/indie, electronica/dance, pop, and rock. In general, the results support Hypothesis 1.

Mood and commercial success (Hypothesis 2)

Hypothesis 2 addressed the pleasantness dimension of the circumplex. As anticipated, although there were several significant relationships between hit popularity and the six moods, Tables 1a-f indicate that the nature of these were not consistent with findings concerning the pleasantness dimension of the circumplex, and so do not support Hypothesis 2. We were less confident that the results would satisfy this second hypothesis, however. Recent findings have described the importance of distinguishing the emotions evoked by music from the affective valence of these emotions, such that, for instance, one might regard a piece of music as distressing, but enjoy that music as a direct consequence of this sadness. In a direct test of this, Schubert (2013) asked participants to select music that they loved and music that they hated, with analyses showing that many participants selected as ‘liked’ music that which evoked negative emotions such as sadness and grief: Schubert argued that, in instances such as these, the emotion valence is of course negative, but crucially that the affective response is separate and positively-valenced. Within this framework, a piece of music regarded as exciting would likely have both a positive emotional valence and a positive affective valence; a piece regarded as boring would likely have both a negative emotional valence and a negative affective valence; but a piece that is enjoyed because it evokes sadness and grief, or any other emotion typically located in the lower half of the pleasantness dimension, would have a negative emotional valence but nonetheless also have a positive affective valence. As such, when the circumplex relates pleasantness to the more specific emotional connotations of that music the approach arguably under-specifies both concepts: specifically, it conflates the emotional and affective valence of a person’s response to the music, such that the latter might rely upon an idiosyncratic, cognitive component that is subject to wide-ranging individual differences. The same argument applies also the use of sales data in the present research as a proxy for the pleasantness dimension. However, even if one questions the validity of the pleasantness dimension of the circumplex (or of sales data as a proxy for the pleasantness dimension) as a true measure of the valence of a particular affective response, this aspect of the present dataset also allows us to address a different question of considerable practical relevance, namely the potential correlation between music sales and the expression of certain emotions: across all music of any commercial relevance in the United Kingdom, the research can determine which musical emotions are most popular.

In the light of this argument, there are three interpretations of the results concerning Hypothesis 2. The first is that the measure is a valid representation of the pleasantness dimension of the circumplex and that the latter is not related to emotion as predicted. The second is that the moods employed in the research (which were, in effect, determined by the music industry) do not represent a range of states along the continuum of the valence dimension of the circumplex. The third is that hit popularity is not an adequate representation of the pleasantness dimension of the circumplex. Of these explanations we favor the latter two, and particularly the third, for reasons set out immediately above. As such, it may well be crass to argue that the current measure of hit popularity truly captures the pleasantness dimension of the circumplex and/or the emotional and affective valence of responses to the music: neither, of course, do the present results provide strong support for the pleasantness dimension of the circumplex model.

Nonetheless, the relationships that do exist between hit popularity and mood do provide a fascinating insight into the emotional connotations of pieces that enjoy greater commercial success. Although the effect sizes were very small, the overall dataset shows significant, positive relationships between hit popularity and each of moods 1 (clean, simple, relaxing), 4 (mystery, luxury, comfort), and 6 (calm, peace, tranquility); but negative relationships between hit popularity and each of moods 2 (happy, hopeful, ambition), 3 (passion, romance, power), and 5 (energetic, bold, outgoing), such that the former moods are associated with greater commercial success and the latter moods are associated with lower commercial success. Of all these findings, it is particularly interesting that mood 2 (happy, hopeful, ambition) was associated negatively with commercial success, despite the caricature that sales charts and commercial radio airplay are dominated by emotionally upbeat music; and that mood 4 (mystery, luxury, comfort) demonstrated the strongest positive association with commercial success, and mood 5 (energetic, bold, outgoing) demonstrated the strongest negative association with commercial success.

However, these patterns in the overall dataset mask several variations between genres, such that commercial success in one genre appears to require evocation of different moods compared to other genres: more explicitly, the emotion-based criteria of commercial success vary between genres. Mood 1 (clean, simple, relaxing) was associated positively with commercial success in the cases of classical music, electronica/dance, pop, rock, and soul/R&B. Mood 2 (happy, hopeful, ambition) was associated negatively with commercial success in the case of classical music, electronica/dance, pop, and rock. Mood 3 (passion, romance, power) was associated positively with commercial success in the case of electronica/dance, and was associated negatively with commercial success in the case of rock. Mood 4 (mystery, luxury, comfort) was associated positively with commercial success in the case of pop and rock; and negatively with commercial success in the case of alternative/indie and classical music. Mood 5 (energetic, bold, outgoing) was associated negatively with commercial success in the case of country, pop, rock, and soul/R&B. Mood 6 (calm, peace, tranquility) was associated positively with commercial success in the case of rock; and negatively with commercial success in the case of classical music.

Genre and mood

This in turn leads to the subsidiary issue investigated on an exploratory basis by the present research, namely differences between genres in mood. Tables 2a-f indicate a very large number of differences between genres in the moods they connote. For the sake of space, we hesitate to enter into a detailed description of the moods evoked by each genre and where each significant difference lies. However, for the sake of illustration, consider the top line of data in Tables 2a-f, which details the findings concerning alternative/indie. The mean percentage score was 4.56 for mood 1 (clean, simple, relaxing), 8.21 for mood 2 (happy, hopeful, ambition), a 25.68 for mood 3 (passion, romance, power), such that alternative/indie music is not very reflective of mood 1 or 2, and much more likely to convey mood 3 (passion, romance, power) than it is to convey other the other moods. In short, different genres are associated with different moods to differing extents, and this has clear implications for those wishing to use music genre as a means of influencing mood either in either personal, everyday music usage, given recent research showing the importance of perceived control over the music (Krause et al., 2014a); therapeutic settings in which music has health-related effects that are contingent upon reliable induction of mood (Standley, 1995); or in commercial contexts, such as the use of music in advertising or in-store to influence consumers' moods and in turn various aspects of their purchasing behaviors (North and Hargreaves, 2008). The present findings might also provide useful guidance for future work in public health and criminology that has identified elevated mental health problems and juvenile offending among those who listen to certain musical styles, particularly rock and rap: it is noteworthy in this context that Tables 2a-f show that rap/hip hop and rock scored lowest of the musical styles on moods 1 (clean, simple, relaxing) and 6 (calm, peace, tranquility). Also interesting in this context, however, is that classical music scored much lower than the other genres on mood 2 (happy, hopeful, ambition), which may illustrate why the public health research shows associations between musical taste and mental health that are not exclusive to rap and rock music (see e.g., Stack's (2002) evidence concerning suicide acceptance in opera audiences).

Limitations

One of the clear advantages of the archival approach adopted here is the potential to test theory using a very large sample of music and sales information from entire populations. However, inherent to the approach are a number of limitations which deserve attention. First, we have briefly mentioned already the difficulty of testing the pleasantness dimension of the circumplex via archival data. Specifically, while sales charts and radio airplay can provide a population-wide measure of the overall popularity of a given piece, there is an issue with the failure of this measure to distinguish between emotional and affective valence. More fine-grained measures of these two variables, which includes reactions to music at the negative end of the pleasantness dimension, will need to be developed before this aspect of the circumplex model can be tested meaningfully through means such as those employed here. In terms of their ability to speak to the circumplex model, we have much more confidence in conclusions drawn from the present data concerning energy than we do in those concerning pleasantness/chart performance.

Second, as with much of the research on music and emotion, the present methodology is unable to account for any individual differences in emotional reactions to music, and in particular those arising from extrinsic associations that a given piece has for a given listener (or for entire populations through the use of the music in question in, for instance, advertising campaigns). In a similar vein, the current approach to data collection cannot account for the impact of the location of listening on emotional response, despite numerous recent studies associating the two (e.g., Krause et al., 2014b).

Finally, the database of music analyzed was limited to that which had enjoyed popularity in the United Kingdom, such that the present findings cannot speak to music and emotion in other cultures. However, although the findings concerning genre and mood would likely differ cross-culturally, we are optimistic that future research concerning energy and mood in even radically different cultures to those investigated here would yield similar findings, given that Russell (1983) found evidence supporting the circumplex among native speakers of Gujurati, Croatian, Japanese, and Chinese; Russell et al. (1989) found evidence confirming the circumplex model among Chinese participants; and Furrer et al. (2012) found similar in Japan.

Conclusion

The present research has found that the mood of a very large sample of music can be predicted by its energy, which is consistent with the circumplex model of affect. Findings concerning BPM and mood were less clear, although the broadly consistent pattern of findings is what might be expected given that the former is clearly just one of several contributors to the overall arousing qualities of music. Findings concerning hit popularity and mood were more equivocal in their support for the circumplex model, although this might be because the measure failed to adequately capture the difference between emotional and affective valence; and the extensive relationships that do exist between hit popularity and mood provide some interesting insights into the preferences of the audiences for differing genres, and how certain genres place more emphasis on certain moods than others. Aside from their theoretical implications for research on the circumplex and aesthetic responses to music, the findings are potentially relevant to music marketing, and perhaps also to a more limited extent to music therapy, marketing, and the public’s everyday music listening habits.

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Table 1a.

GLMM Analysis Predicting Mood 1 Scores (Clean, Simple, Relaxing)

Analysis variables	*F*	df1	df2	*p*	β	*t*	95% CI		η^2
	Overall Dataset (N = 143353)								
Corrected model	4214.53	3	143349	< .001					
Energy	12544.01	1	143349	< .001	-0.04	-112.00	-0.04	-0.04	0.080
BPM	28.06	1	143349	< .001	0.00	5.30	0.00	0.00	0.000
Hit popularity	14.16	1	143349	< .001	0.16	3.76	0.08	0.25	0.000
	Alternative/ Indie (N = 806)								
Corrected model	60.54	3	802	< .001					
Energy	153.45	1	802	< .001	-0.03	-12.39	-0.04	-0.03	0.161
BPM	9.83	1	802	0.002	-0.01	-3.14	-0.17	0.00	0.012
Hit popularity	0.71	1	802	0.399	0.97	0.84	-1.29	3.24	0.001
	Christian/ Gospel (N =222)								
Corrected model	1.31	3	218	0.273					
Energy	2.83	1	218	0.094	-0.04	-1.68	-0.08	0.01	0.013
BPM	0.54	1	218	0.465	0.01	0.73	-0.02	0.03	0.002
Hit popularity	0.18	1	218	0.673	-1.84	-0.42	-10.43	6.75	0.001
	Classical (N = 4745)								
Corrected model	277.49	3	4741	< .001					
Energy	816.7	1	4741	< .001	-0.26	-28.58	-0.28	-0.24	0.147
BPM	2.49	1	4741	0.114	0.01	1.58	0.00	0.01	0.001
Hit popularity	10.2	1	4741	0.001	6.74	3.19	2.60	10.87	0.002
	Country (N = 2552)								
Corrected model	19.62	3	2548	< .001					
Energy	53.89	1	2548	< .001	-0.03	-7.34	-0.03	-0.02	0.021
BPM	2.47	1	2548	0.116	0.00	-1.57	-0.01	0.00	0.001
Hit popularity	0.49	1	2548	0.483	0.58	0.70	-1.04	2.19	0.000
	Electronica/ Dance (N = 16086)								
Corrected model	84.74	3	16082	< .001					
Energy	8.86	1	16082	0.003	0.00	2.98	0.00	0.00	0.001
BPM	215.87	1	16082	< .001	0.01	14.69	0.01	0.01	0.013
Hit popularity	10.79	1	16082	0.001	0.32	3.29	0.13	0.51	0.001
	Folk (N = 992)								
Corrected model	43.72	3	988	< .001					
Energy	131.09	1	988	< .001	-0.08	-11.45	-0.09	-0.06	0.117
BPM	0.16	1	988	0.692	0.00	0.40	-0.01	0.01	0.000
Hit popularity	0.3	1	988	0.583	-0.36	-0.55	-1.65	0.93	0.000
	Jazz (N = 4300)								
Corrected model	67.05	3	4296	< .001					
Energy	168.95	1	4296	< .001	-0.10	-13.00	-0.12	-0.09	0.038
BPM	11.56	1	4296	0.001	-0.01	-3.40	-0.02	-0.01	0.003
Hit popularity	0.11	1	4296	0.746	-0.58	-0.32	-4.12	2.96	0.000
	Latin (N = 633)								
Corrected model	13.13	3	629	< .001					

Energy	36.36	1	629	< .001	-0.02	-6.03	-0.02	-0.01	0.055
BPM	3.09	1	629	0.079	-0.01	-1.76	-0.01	0.00	0.005
Hit popularity	0.05	1	629	0.829	0.10	0.22	-0.77	0.96	0.000
	Pop (N = 58250)								
Corrected model	806.24	3	58246	< .001					
Energy	2095.14	1	58246	< .001	-0.02	-45.77	-0.02	-0.02	0.035
BPM	176.53	1	58246	< .001	-0.01	-13.29	-0.01	-0.01	0.003
Hit popularity	24.99	1	58246	< .001	0.17	5.00	0.10	0.23	0.000
	Rap/ Hip hop (N = 8296)								
Corrected model	2.3	3	8292	0.075					
Energy	2.96	1	8292	0.085	0.00	-1.72	0.00	0.00	0.000
BPM	0.3	1	8292	0.584	0.00	-0.55	0.00	0.00	0.000
Hit popularity	3.65	1	8292	0.056	0.08	1.91	0.00	0.17	0.000
	Reggae/ Ska (N = 215)								
Corrected model	1.94	3	211	0.124					
Energy	2.89	1	211	0.091	0.01	1.70	0.00	0.02	0.014
BPM	0.05	1	211	0.817	0.00	-0.23	-0.01	0.01	0.000
Hit popularity	2.49	1	211	0.116	5.55	3.51	-1.38	12.47	0.055
	Rock (N = 44307)								
Corrected model	323.55	3	44303	< .001					
Energy	730.25	1	44303	< .001	-0.01	-27.02	-0.01	-0.01	0.016
BPM	137.05	1	44303	< .001	0.00	-11.71	0.00	0.00	0.003
Hit popularity	45.49	1	44303	< .001	0.36	6.74	0.26	0.47	0.001
	Soul/ R&B (N = 869)								
Corrected model	28.19	3	865	< .001					
Energy	64.25	1	865	< .001	-0.02	-8.02	-0.02	-0.01	0.069
BPM	2.99	1	865	0.084	0.00	-1.73	-0.01	0.00	0.003
Hit popularity	12.05	1	865	0.001	2.10	3.47	0.91	3.28	0.014
	Soundtracks (N = 406)								
Corrected model	8.6	3	402	< .001					
Energy	14.13	1	402	< .001	-0.13	-3.76	-0.20	-0.06	0.034
BPM	0.47	1	402	0.493	0.01	0.69	-0.01	0.03	0.001
Hit popularity	7.72	1	402	0.006	26.62	2.78	7.79	45.46	0.019
	World (N = 542)								
Corrected model	21.49	3	538	< .001					
Energy	61.46	1	538	< .001	-0.06	-7.84	-0.07	-0.04	0.103
BPM	2.09	1	538	0.149	0.01	1.45	0.00	0.03	0.004
Hit popularity	0.76	1	538	0.385	2.81	0.87	-3.54	9.16	0.001

Note. DF = degrees of freedom; CI = confidence interval.

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Table 1b.

GLMM Analysis Predicting Mood 2 Scores (Happy, Hopeful, Ambition)

Analysis variables	*F*	df1	df2	*p*	β	*t*	95% CI		η^2
	Overall Dataset (N = 143353)								
Corrected model	3855.90	3	143349	< .001					
Energy	10962.94	1	143349	< .001	-0.04	-104.70	-0.04	-0.04	0.071
BPM	54.06	1	143349	< .001	0.00	-7.35	0.00	0.00	0.000
Hit popularity	94.39	1	143349	< .001	-0.43	-9.72	-0.52	-0.34	0.001
	Alternative/ Indie (N = 806)								
Corrected model	3.39	3	802	< .001					
Energy	4.64	1	802	0.032	0.01	2.15	0.00	0.01	0.006
BPM	1.02	1	802	0.314	0.00	-1.01	-0.01	0.00	0.001
Hit popularity	4.83	1	802	0.028	-2.68	-2.20	-5.06	-0.29	0.006
	Christian/ Gospel (N = 222)								
Corrected model	0.78	3	218	0.504					
Energy	1.90	1	218	0.169	0.03	1.38	-0.01	0.06	0.009
BPM	0.01	1	218	0.924	0.00	0.10	-0.02	0.02	0.000
Hit popularity	0.84	1	218	0.360	-3.16	-0.92	-9.94	3.62	0.004
	Classical/ Opera (N = 4745)								
Corrected model	68.25	3	4741	< .001					
Energy	18.72	1	4741	< .001	0.05	13.59	0.04	0.05	0.038
BPM	0.76	1	4741	0.384	0.00	0.87	0.00	0.00	0.000
Hit popularity	15.50	1	4741	< .001	-3.09	-3.94	-4.64	-1.55	0.003
	Country (N = 2552)								
Corrected model	22.02	3	2548	< .001					
Energy	47.02	1	2548	< .001	0.04	6.86	0.03	0.05	0.018
BPM	13.03	1	2548	< .001	0.01	3.61	0.01	0.02	0.005
Hit popularity	1.55	1	2548	0.214	1.44	1.24	-0.83	3.70	0.001
	Electronica/ Dance (N = 16086)								
Corrected model	123.68	3	16082	< .001					
Energy	94.39	1	16082	< .001	-0.01	-9.72	-0.01	-0.01	0.006
BPM	212.98	1	16082	< .001	-0.02	-14.59	-0.02	-0.01	0.013
Hit popularity	12.33	1	16082	< .001	-0.72	-3.51	-1.13	-0.32	0.001
	Folk (N = 992)								
Corrected model	73.38	3	988	< .001					
Energy	217.79	1	988	< .001	0.12	14.76	0.11	0.14	0.181
BPM	0.33	1	988	0.568	0.00	0.57	-0.01	0.01	0.000
Hit popularity	0.00	1	988	0.949	-0.05	-0.06	-1.66	1.55	0.000
	Jazz (N = 4300)								
Corrected model	374.44	3	4296	< .001					
Energy	985.13	1	4296	< .001	0.69	31.39	0.16	0.18	0.187
BPM	25.51	1	4296	< .001	0.01	5.05	0.01	0.02	0.006
Hit popularity	9.73	1	4296	0.002	-3.92	-3.12	-6.38	-1.46	0.002
	Latin (N = 633)								
Corrected model	10.85	3	629	< .001					

Energy	22.03	1	629	< .001	-0.03	-4.69	-0.04	-0.01	0.034
BPM	8.59	1	629	0.004	0.02	2.93	0.01	0.03	0.013
Hit popularity	0.95	1	629	0.330	-0.81	-0.98	-2.43	0.82	0.002
	Pop (N = 58250)								
Corrected model	407.83	3	58246	< .001					
Energy	953.41	1	58246	< .001	-0.02	-30.88	-0.02	-0.02	0.016
BPM	253.07	1	58246	< .001	0.01	15.91	0.01	0.01	0.004
Hit popularity	82.13	1	58246	< .001	-0.49	-9.06	-0.59	-0.38	0.001
	Rap/ Hip hop (N = 8296)								
Corrected model	12.92	3	8292	< .001					
Energy	11.62	1	8292	0.001	-0.01	-3.41	-0.01	0.00	0.001
BPM	17.73	1	8292	< .001	-0.01	-4.21	-0.01	0.00	0.002
Hit popularity	9.00	1	8292	0.003	-0.35	-3.00	-0.58	-0.12	0.001
	Reggae/ Ska (N = 215)								
Corrected model	3.76	3	211	0.012					
Energy	5.91	1	211	0.016	-0.06	-2.43	-0.10	-0.01	0.027
BPM	1.20	1	211	0.275	0.02	1.09	-0.01	0.05	0.006
Hit popularity	3.75	1	211	0.054	-26.00	-1.94	-52.46	0.47	0.017
	Rock (N = 44307)								
Corrected model	3028.43	3	44303	< .001					
Energy	8933.37	1	44303	< .001	-0.05	-94.52	-0.05	-0.05	0.168
BPM	0.03	1	44303	0.867	0.00	-0.17	0.00	0.00	0.000
Hit popularity	37.99	1	44303	< .001	-0.63	-6.16	-0.84	-0.43	0.001
	Soul/ R&B (N = 869)								
Corrected model	11.38	3	865	< .001					
Energy	14.36	1	865	< .001	0.03	3.79	0.01	0.04	0.016
BPM	7.09	1	865	0.008	0.01	2.66	0.00	0.02	0.008
Hit popularity	9.44	1	865	0.002	-5.73	-3.07	-9.39	-2.07	0.011
	Soundtracks (N = 406)								
Corrected model	11.50	3	402	< .001					
Energy	22.95	1	402	< .001	0.09	4.79	0.05	0.12	0.054
BPM	1.28	1	402	0.259	-0.01	-1.13	-0.02	0.01	0.003
Hit popularity	5.81	1	402	0.016	-12.24	-2.41	-22.23	-2.26	0.014
	World (N = 542)								
Corrected model	7.11	3	538	< .001					
Energy	19.37	1	538	< .001	0.03	4.40	0.02	0.05	0.035
BPM	0.01	1	538	0.923	0.00	-0.10	-0.01	0.01	0.000
Hit popularity	2.26	1	538	0.134	-4.63	-1.50	-10.69	1.43	0.004

Note. DF = degrees of freedom; CI = confidence interval.

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Table 1c.

GLMM Analysis Predicting Mood 3 Scores (Passion, Romance, Power)

Analysis variables	*F*	df1	df2	*p*	β	*t*	95% CI		η^2
	Overall Dataset (N = 143353)								
Corrected model	18440.83	3	143349	< .001					
Energy	52437.41	1	143349	< .001	0.15	228.99	0.15	0.15	0.268
BPM	502.58	1	143349	< .001	0.02	22.42	0.02	0.02	0.003
Hit popularity	25.44	1	143349	< .001	-0.42	-5.04	-0.58	-0.26	0.000
	Alternative/ Indie (N = 806)								
Corrected model	272.50	3	802	< .001					
Energy	720.15	1	802	< .001	0.17	26.84	0.16	0.18	0.473
BPM	29.58	1	802	< .001	0.05	5.44	0.03	0.06	0.036
Hit popularity	0.30	1	802	0.582	-1.59	-0.55	-7.25	4.07	0.000
	Christian/ Gospel (N = 222)								
Corrected model	15.17	3	218	< .001					
Energy	29.41	1	218	< .001	0.14	5.42	0.09	0.20	0.119
BPM	0.45	1	218	0.502	0.01	0.67	-0.02	0.04	0.002
Hit popularity	7.47	1	218	0.007	13.71	2.73	3.82	23.59	0.033
	Classical/ Opera (N = 4745)								
Corrected model	351.79	3	4741	< .001					
Energy	1047.66	1	4741	< .001	0.18	32.37	0.17	0.19	0.181
BPM	0.22	1	4741	0.638	0.00	-0.47	-0.01	0.00	0.000
Hit popularity	3.82	1	4741	0.051	-2.56	-1.95	-5.14	0.01	0.001
	Country (N = 2552)								
Corrected model	173.17	3	2548	< .001					
Energy	490.56	1	2548	< .001	0.15	22.15	0.13	0.16	0.161
BPM	12.39	1	2548	< .001	0.01	3.52	0.01	0.02	0.005
Hit popularity	2.33	1	2548	0.127	-2.29	-1.53	-5.23	0.65	0.001
	Electronica/ Dance (N = 16086)								
Corrected model	1675.83	3	16082	< .001					
Energy	4883.12	1	16082	< .001	0.09	69.88	0.09	0.10	0.233
BPM	1.81	1	16082	0.178	0.00	-1.35	0.00	0.00	0.000
Hit popularity	36.73	1	16082	< .001	1.52	6.06	1.03	2.01	0.002
	Folk (N = 992)								
Corrected model	66.15	3	988	< .001					
Energy	193.41	1	988	< .001	0.14	13.91	0.12	0.16	0.164
BPM	0.89	1	988	0.346	0.01	0.94	-0.01	0.02	0.001
Hit popularity	0.76	1	988	0.385	-0.84	-0.87	-2.75	1.06	0.001
	Jazz (N = 4300)								
Corrected model	293.05	3	4296	< .001					
Energy	799.98	1	4296	< .001	0.14	28.28	0.13	0.15	0.157
BPM	15.96	1	4296	< .001	0.01	4.00	0.00	0.01	0.004
Hit popularity	0.72	1	4296	0.396	0.98	0.85	-1.29	3.25	0.000
	Latin (N = 633)								
Corrected model	43.84	3	629	< .001					

Energy	125.33	1	629	< .001	0.07	11.20	0.06	0.09	0.166
BPM	0.32	1	629	0.572	0.00	-0.57	-0.02	0.01	0.001
Hit popularity	2.65	1	629	0.104	1.63	1.63	-0.34	3.60	0.004
	Pop (N = 58250)								
Corrected model	3777.21	3	58246	< .001					
Energy	10973.65	1	58246	< .001	0.10	104.76	0.09	0.10	0.159
BPM	80.10	1	58246	< .001	0.01	8.95	0.01	0.01	0.001
Hit popularity	0.00	1	58246	0.979	0.00	-0.03	-0.15	0.15	0.000
	Rap/ Hip hop (N = 8296)								
Corrected model	1067.68	3	8292	< .001					
Energy	3188.49	1	8292	< .001	0.07	56.47	0.07	0.08	0.278
BPM	2.08	1	8292	0.149	0.00	1.44	0.00	0.00	0.000
Hit popularity	8.70	1	8292	0.003	0.28	2.95	0.10	0.47	0.001
	Reggae/ Ska (N = 215)								
Corrected model	17.09	3	211	< .001					
Energy	49.66	1	211	< .001	0.06	7.05	0.05	0.08	0.191
BPM	0.05	1	211	0.829	0.00	0.22	-0.01	0.01	0.000
Hit popularity	0.21	1	211	0.651	2.37	0.45	-7.95	12.68	0.001
	Rock (N = 44307)								
Corrected model	5700.66	3	44303	< .001					
Energy	16293.03	1	44303	< .001	0.14	127.64	0.14	0.14	0.269
BPM	282.19	1	44303	< .001	0.02	16.80	0.02	0.02	0.006
Hit popularity	20.86	1	44303	< .001	-0.97	-4.57	-1.39	-0.56	0.000
	Soul/ R&B (N = 869)								
Corrected model	36.61	3	865	< .001					
Energy	85.35	1	865	< .001	0.10	9.24	0.08	0.12	0.090
BPM	7.78	1	865	0.005	0.02	2.79	0.01	0.04	0.009
Hit popularity	7.86	1	865	0.005	-7.85	-2.80	-13.35	-2.35	0.009
	Soundtracks (N = 406)								
Corrected model	18.23	3	402	< .001					
Energy	49.85	1	402	< .001	0.24	7.06	0.17	0.30	0.110
BPM	0.27	1	402	0.607	-0.01	-0.51	-0.03	0.01	0.001
Hit popularity	0.98	1	402	0.323	-9.20	-0.99	-27.45	9.06	0.002
	World (N = 542)								
Corrected model	22.64	3	538	< .001					
Energy	64.46	1	538	< .001	0.07	8.03	0.06	0.09	0.107
BPM	3.97	1	538	0.047	0.02	1.99	0.00	0.04	0.007
Hit popularity	0.07	1	538	0.797	1.02	0.26	-6.78	8.83	0.000

Note. DF = degrees of freedom; CI = confidence interval.

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Table 1d.

GLMM Analysis Predicting Mood 4 Scores (Mystery, Luxury, Comfort)

Analysis variables	*F*	df1	df2	*p*	β	*t*	95% CI		η^2
	Overall Dataset (N = 143353)								
Corrected model	5496.7	3	143349	< .001					
Energy	14731.71	1	143349	< .001	-0.04	-121.37	-0.04	-0.04	0.093
BPM	621.82	1	143349	< .001	-0.01	-24.94	-0.10	-0.01	0.004
Hit popularity	50.77	1	143349	< .001	0.30	7.13	0.22	0.38	0.000
	Alternative/ Indie (N = 806)								
Corrected model	18.84	3	802	< .001					
Energy	22.58	1	802	< .001	-0.01	-4.75	-0.02	-0.01	0.027
BPM	18.11	1	802	< .001	-0.02	-4.26	-0.02	-0.01	0.022
Hit popularity	6.63	1	802	0.010	3.39	2.58	0.81	5.98	0.008
	Christian/ Gospel (N =222)								
Corrected model	2.05	3	218	0.108					
Energy	0.37	1	218	0.543	-0.01	-0.61	-0.06	0.03	0.002
BPM	1.57	1	218	0.212	-0.02	-1.25	-0.04	0.01	0.007
Hit popularity	3.61	1	218	0.059	-8.41	-1.90	-17.12	0.31	0.016
	Classical (N = 4745)								
Corrected model	20.37	3	4741	< .001					
Energy	47.79	1	4741	< .001	-0.04	-6.91	-0.05	-0.03	0.010
BPM	1.17	1	4741	0.280	0.00	-1.08	-0.01	0.00	0.000
Hit popularity	13.25	1	4741	< .001	-5.03	-3.64	-7.74	-2.32	0.003
	Country (N = 2552)								
Corrected model	22.09	3	2548	< .001					
Energy	49.72	1	2548	< .001	-0.04	-7.05	-0.05	-0.03	0.019
BPM	10.62	1	2548	0.001	-0.01	-3.26	-0.02	-0.01	0.004
Hit popularity	2.2	1	2548	0.138	1.96	1.48	-0.63	4.55	0.001
	Electronica/ Dance (N = 16086)								
Corrected model	1019.85	3	16082	< .001					
Energy	2549.68	1	16082	< .001	-0.04	-50.49	-0.04	-0.04	0.137
BPM	221.66	1	16082	< .001	-0.01	-14.89	-0.01	-0.01	0.014
Hit popularity	0.03	1	16082	0.861	0.03	0.18	-0.28	0.33	0.000
	Folk (N = 992)								
Corrected model	20.06	3	988	< .001					
Energy	59.55	1	988	< .001	-0.07	-7.72	-0.09	-0.05	0.057
BPM	0	1	988	0.995	0.00	0.01	-0.01	0.01	0.000
Hit popularity	0.13	1	988	0.715	0.32	0.37	-1.41	2.06	0.000
	Jazz (N = 4300)								
Corrected model	171.62	3	4296	< .001					
Energy	489.87	1	4296	< .001	-0.19	-22.13	-0.21	-0.17	0.102
BPM	1.54	1	4296	0.214	0.00	-1.24	-0.01	0.00	0.000
Hit popularity	1.43	1	4296	0.232	-2.38	-1.20	-6.27	1.52	0.000
	Latin (N = 633)								
Corrected model	21.3	3	629	< .001					

Energy	62.48	1	629	< .001	-0.04	-7.90	-0.05	-0.03	0.090
BPM	1.28	1	629	0.259	0.01	1.13	-0.01	0.02	0.002
Hit popularity	0.1	1	629	0.757	0.24	0.31	-1.30	1.79	0.000
	Pop (N = 58250)								
Corrected model	958.37	3	58246	< .001					
Energy	2613.39	1	58246	< .001	-0.03	-51.12	-0.03	-0.03	0.043
BPM	122.61	1	58246	< .001	-0.01	-11.07	-0.01	-0.01	0.002
Hit popularity	20.72	1	58246	< .001	0.23	4.55	0.13	0.33	0.000
	Rap/ Hip hop (N = 8296)								
Corrected model	375.62	3	8292	< .001					
Energy	1087.56	1	8292	< .001	-0.04	-32.98	-0.04	-0.03	0.116
BPM	34.69	1	8292	< .001	-0.01	-5.89	-0.01	0.00	0.004
Hit popularity	0.02	1	8292	0.895	0.01	0.13	-0.15	0.17	0.000
	Reggae/ Ska (N = 215)								
Corrected model	1.73	3	211	0.162					
Energy	4.47	1	211	0.036	-0.03	-2.11	-0.06	0.00	0.021
BPM	0.43	1	211	0.512	-0.01	-0.66	-0.03	0.01	0.002
Hit popularity	0.01	1	211	0.919	0.84	0.10	-15.30	16.98	0.000
	Rock (N = 44307)								
Corrected model	136.01	3	44303	< .001					
Energy	14.7	1	44303	< .001	0.00	3.83	0.00	0.00	0.000
BPM	303.24	1	44303	< .001	-0.01	-17.41	-0.01	-0.01	0.007
Hit popularity	91.24	1	44303	< .001	0.77	9.55	0.61	0.92	0.002
	Soul/ R&B (N = 869)								
Corrected model	38.7	3	865	< .001					
Energy	107.9	1	865	< .001	-0.09	-10.39	-0.10	-0.07	0.111
BPM	1.69	1	865	0.194	-0.01	-1.30	-0.02	0.00	0.002
Hit popularity	0.9	1	865	0.343	2.02	0.95	-2.16	6.21	0.001
	Soundtracks (N = 406)								
Corrected model	6.3	3	402	< .001					
Energy	18.14	1	402	< .001	-0.08	-4.26	-0.12	-0.04	0.043
BPM	0.44	1	402	0.508	0.00	-0.66	-0.02	0.01	0.001
Hit popularity	1.83	1	402	0.177	-6.97	-1.35	-17.11	3.17	0.005
	World (N = 542)								
Corrected model	30.75	3	538	< .001					
Energy	88.59	1	538	< .001	-0.09	-9.41	-0.10	-0.07	0.141
BPM	0.58	1	538	0.445	-0.01	-0.76	-0.02	0.01	0.001
Hit popularity	2.57	1	538	0.110	-6.36	-1.60	-14.15	1.44	0.005

Note. DF = degrees of freedom; CI = confidence interval.

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Table 1e.

GLMM Analysis Predicting Mood 5 Scores (Energetic, Bold, Outgoing)

Analysis variables	*F*	df1	df2	*p*	β	*t*	95% CI		η^2
	Overall Dataset (N = 143353)								
Corrected model	2884.50	3	143349	< .001					
Energy	8435.54	1	143349	< .001	0.04	91.85	0.04	0.05	0.056
BPM	1.74	1	143349	0.187	0.00	-1.32	0.00	0.00	0.000
Hit popularity	131.77	1	143349	< .001	-0.68	-11.48	-0.80	-0.57	0.001
	Alternative/ Indie (N = 806)								
Corrected model	48.23	3	802	< .001					
Energy	113.25	1	802	< .001	0.04	10.64	0.03	0.05	0.124
BPM	7.20	1	802	0.007	0.01	2.68	0.00	0.02	0.009
Hit popularity	8.99	1	802	0.003	-5.13	-3.00	-8.48	-1.77	0.011
	Christian/ Gospel (N = 222)								
Corrected model	8.38	3	218	< .001					
Energy	24.27	1	218	< .001	0.10	4.93	0.06	0.14	0.100
BPM	0.01	1	218	0.918	0.00	-0.10	-0.02	0.02	0.000
Hit popularity	3.65	1	218	0.057	-7.40	-1.91	-15.03	0.23	0.016
	Classical/ Opera (N = 4745)								
Corrected model	412.89	3	4741	< .001					
Energy	1233.72	1	4741	< .001	0.11	35.12	0.11	0.12	0.206
BPM	1.60	1	4741	0.206	0.00	1.26	0.00	0.01	0.000
Hit popularity	0.03	1	4741	0.864	0.13	0.17	-1.34	1.60	0.000
	Country (N = 2552)								
Corrected model	23.96	3	2548	< .001					
Energy	36.26	1	2548	< .001	0.04	6.02	0.03	0.05	0.014
BPM	9.20	1	2548	0.002	0.01	3.03	0.00	0.02	0.004
Hit popularity	23.85	1	2548	< .001	-6.76	-4.88	-9.48	-4.05	0.009
	Electronica/ Dance (N = 16086)								
Corrected model	1183.01	3	16082	< .001					
Energy	3503.77	1	16082	< .001	0.09	59.19	0.09	0.10	0.179
BPM	233.17	1	16082	< .001	-0.02	-15.27	-0.03	-0.02	0.014
Hit popularity	6.82	1	16082	0.009	-0.78	-2.61	-1.36	-0.19	0.000
	Folk (N = 992)								
Corrected model	129.24	3	988	< .001					
Energy	380.91	1	988	< .001	0.19	19.52	0.17	0.21	0.278
BPM	1.19	1	988	0.277	0.01	1.09	-0.01	0.02	0.001
Hit popularity	0.43	1	988	0.513	-0.62	-0.65	-2.48	1.24	0.000
	Jazz (N = 4300)								
Corrected model	452.65	3	4296	< .001					
Energy	1245.65	1	4296	< .001	0.21	35.29	0.20	0.22	0.225
BPM	15.86	1	4296	< .001	0.01	3.98	0.01	0.02	0.004
Hit popularity	0.92	1	4296	0.337	-1.33	-0.96	-4.04	1.38	0.000
	Latin (N = 633)								
Corrected model	27.91	3	629	< .001					

Energy	81.74	1	629	< .001	0.07	9.04	0.06	0.09	0.115
BPM	0.59	1	629	0.443	0.01	0.77	-0.01	0.03	0.001
Hit popularity	3.29	1	629	0.070	-2.28	-1.81	-4.75	0.19	0.005
	Pop (N = 58250)								
Corrected model	2680.01	3	58246	< .001					
Energy	7307.93	1	58246	< .001	0.07	85.49	0.07	0.07	0.111
BPM	315.95	1	58246	< .001	0.02	17.78	0.02	0.02	0.005
Hit popularity	110.60	1	58246	< .001	-0.76	-10.52	-0.90	-0.62	0.002
	Rap/ Hip hop (N = 8296)								
Corrected model	412.67	3	8292	< .001					
Energy	1234.03	1	8292	< .001	0.07	35.13	0.06	0.07	0.130
BPM	0.84	1	8292	0.359	0.00	-0.92	-0.01	0.00	0.000
Hit popularity	4.32	1	8292	0.038	-0.30	-2.08	-0.59	-0.02	0.001
	Reggae/ Ska (N = 215)								
Corrected model	3.29	3	211	0.022					
Energy	0.13	1	211	0.715	0.01	0.37	-0.03	0.04	0.001
BPM	4.49	1	211	0.035	0.03	2.12	0.00	0.06	0.021
Hit popularity	4.96	1	211	0.027	-24.59	-2.23	-46.36	-2.82	0.023
	Rock (N = 44307)								
Corrected model	93.33	3	44303	< .001					
Energy	187.37	1	44303	< .001	-0.01	-13.69	-0.01	-0.01	0.004
BPM	15.27	1	44303	< .001	0.00	3.91	0.00	0.00	0.000
Hit popularity	77.35	1	44303	< .001	-1.29	-8.80	-1.58	-1.00	0.002
	Soul/ R&B (N = 869)								
Corrected model	112.47	3	865	< .001					
Energy	313.07	1	865	< .001	0.17	17.69	0.16	0.19	0.266
BPM	0.92	1	865	0.339	0.01	0.96	-0.01	0.02	0.001
Hit popularity	12.60	1	865	< .001	-8.82	-3.55	-13.69	-3.94	0.014
	Soundtracks (N = 406)								
Corrected model	15.40	3	402	< .001					
Energy	36.06	1	402	< .001	0.11	6.01	-0.09	-5.29	0.082
BPM	4.35	1	402	0.038	-0.01	-2.09	-0.01	-2.70	0.011
Hit popularity	1.10	1	402	0.296	-5.33	-1.05	-3.80	-0.79	0.003
	World (N = 542)								
Corrected model	36.29	3	538	< .001					
Energy	106.81	1	538	< .001	0.09	10.34	0.07	0.11	0.166
BPM	0.45	1	538	0.505	0.01	0.67	-0.01	0.02	0.001
Hit popularity	2.62	1	538	0.106	-6.08	-1.62	-13.46	1.30	0.005

Note. DF = degrees of freedom; CI = confidence interval.

Table 1f.

GLMM Analysis Predicting Mood 6 Scores (Calm, Peace, Tranquility)

Analysis variables	*F*	df1	df2	*p*	β	*t*	95% CI		η^2
	Overall Dataset (N = 143353)								
Corrected model	19221.98	3	143349	< .001					
Energy	54609.07	1	143349	< .001	-0.08	-233.69	-0.08	-0.08	0.276
BPM	539.11	1	143349	< .001	-0.01	-23.22	-0.01	-0.01	0.004
Hit popularity	0.24	1	143349	0.626	0.02	0.49	-0.06	0.10	0.000
	Alternative/ Indie (N = 806)								
Corrected model	207.89	3	802	< .001					
Energy	543.71	1	802	< .001	-0.08	-23.32	-0.09	-0.07	0.404
BPM	19.03	1	802	< .001	-0.02	-4.36	-0.03	-0.01	0.023
Hit popularity	7.94	1	802	0.005	4.30	2.82	1.30	7.29	0.010
	Christian/ Gospel (N = 222)								
Corrected model	16.62	3	218	< .001					
Energy	41.16	1	218	< .001	-0.14	-6.42	-0.18	-0.09	0.159
BPM	0.05	1	218	0.821	0.00	0.23	-0.02	0.03	0.000
Hit popularity	2.46	1	218	0.119	-6.33	-1.57	-14.28	1.63	0.011
	Classical/ Opera (N = 4745)								
Corrected model	41.21	3	4741	< .001					
Energy	83.29	1	4741	< .001	-0.04	-9.13	-0.05	-0.03	0.017
BPM	28.22	1	4741	< .001	0.00	-5.31	-0.02	-0.01	0.006
Hit popularity	12.53	1	4741	< .001	-3.71	-3.54	-5.76	-1.65	0.003
	Country (N = 2552)								
Corrected model	79.50	3	2548	< .001					
Energy	218.84	1	2548	< .001	-0.11	-14.79	-0.13	-0.10	0.079
BPM	8.18	1	2548	0.004	-0.01	-2.86	-0.02	0.00	0.003
Hit popularity	4.50	1	2548	0.034	3.65	2.12	0.28	7.01	0.002
	Electronica/ Dance (N = 16086)								
Corrected model	537.77	3	16082	< .001					
Energy	1367.78	1	16082	< .001	-0.03	-36.98	-0.03	-0.02	0.078
BPM	100.83	1	16082	< .001	-0.01	-10.04	-0.01	-0.01	0.006
Hit popularity	3.67	1	16082	0.055	0.25	1.92	-0.01	0.50	0.000
	Folk (N = 992)								
Corrected model	127.53	3	988	< .001					
Energy	379.35	1	988	< .001	-0.21	-19.48	-0.23	-0.19	0.277
BPM	0.21	1	988	0.646	0.00	-0.46	-0.02	0.01	0.000
Hit popularity	0.03	1	988	0.870	0.17	0.16	-1.88	2.23	0.000
	Jazz (N = 4300)								
Corrected model	152.59	3	4296	< .001					
Energy	417.75	1	4296	< .001	-0.16	-20.44	-0.18	-0.15	0.089
BPM	6.05	1	4296	0.014	-0.01	-2.46	-0.02	0.00	0.001
Hit popularity	0.46	1	4296	0.499	1.26	0.68	-2.39	4.92	0.000
	Latin (N = 633)								
Corrected model	113.11	3	629	< .001					

Energy	337.22	1	629	< .001	-0.11	-18.36	-0.12	-0.10	0.349
BPM	2.27	1	629	0.132	-0.01	-1.51	-0.02	0.00	0.004
Hit popularity	0.90	1	629	0.342	0.87	0.95	-0.93	2.68	0.001
	Pop (N = 58250)								
Corrected model	8648.64	3	58246	< .001					
Energy	25121.46	1	58246	< .001	-0.10	-158.50	-0.10	-0.09	0.301
BPM	188.08	1	58246	< .001	-0.01	-13.71	-0.01	-0.01	0.003
Hit popularity	0.44	1	58246	0.507	0.03	0.66	-0.07	0.13	0.000
	Rap/ Hip hop (N = 8296)								
Corrected model	210.19	3	8292	< .001					
Energy	616.20	1	8292	< .001	-0.03	-24.82	-0.03	-0.02	0.069
BPM	7.52	1	8292	0.006	0.00	-2.74	-0.01	0.00	0.001
Hit popularity	4.72	1	8292	0.030	-0.16	-2.17	-0.31	-0.02	0.001
	Reggae/ Ska (N = 215)								
Corrected model	18.47	3	211	< .001					
Energy	42.83	1	211	< .001	-0.11	-6.54	-0.14	-0.08	0.169
BPM	6.08	1	211	0.014	-0.03	-2.47	-0.05	-0.01	0.028
Hit popularity	1.91	1	211	0.169	-13.55	-1.38	-32.89	5.78	0.009
	Rock (N = 44307)								
Corrected model	2833.91	3	44303	< .001					
Energy	8013.60	1	44303	< .001	-0.04	-89.52	-0.04	-0.04	0.153
BPM	184.57	1	44303	< .001	-0.01	-13.59	-0.01	-0.01	0.004
Hit popularity	37.69	1	44303	< .001	0.57	6.14	0.39	0.75	0.001
	Soul/ R&B (N = 869)								
Corrected model	53.82	3	865	< .001					
Energy	160.16	1	865	< .001	-0.09	-12.66	-0.11	-0.08	0.156
BPM	0.31	1	865	0.577	0.00	0.56	-0.01	0.01	0.000
Hit popularity	0.16	1	865	0.691	-0.75	-0.40	-4.45	2.95	0.000
	Soundtracks (N = 406)								
Corrected model	10.96	3	402	< .001					
Energy	27.93	1	402	< .001	-0.09	-5.29	-0.13	-0.06	0.065
BPM	7.28	1	402	0.007	-0.01	-2.70	-0.02	0.00	0.018
Hit popularity	0.63	1	402	0.429	-3.80	-0.79	-13.24	5.63	0.002
	World (N = 542)								
Corrected model	66.30	3	538	< .001					
Energy	197.04	1	538	< .001	-0.10	-14.04	-0.11	-0.08	0.268
BPM	2.51	1	538	0.113	-0.01	-1.59	-0.02	0.00	0.005
Hit popularity	0.03	1	538	0.867	-0.50	-0.17	-6.37	5.36	0.000

Note. DF = degrees of freedom; CI = confidence interval.

Table 2a.

Means, Standard Errors, 95% Confidence Intervals, and Deviation Contrasts for the GLMM Analysis Concerning Genre Predicting Mood 1

					Deviation contrast: Genre compared to the mean				
Genre label	M	SE	95% CI		*t*	*p*	95% CI		η^2
Alternative/ Indie	4.56	0.18	4.21	4.90	-18.00	< .001	-3.54	-2.84	0.002
Children's	5.85	0.57	4.73	6.98	-3.48	.001	-2.96	-0.83	0.000
Christian/ Gospel	7.37	0.33	6.71	8.02	-1.19	.236	-1.01	0.25	0.000
Classical/ Opera	31.62	0.07	31.48	31.76	252.92	< .001	23.69	24.06	0.256
Country	4.60	0.10	4.40	4.79	-27.77	< .001	-3.37	-2.93	0.004
Electronica/Dance	3.33	0.04	3.25	3.41	-58.63	< .001	-4.56	-4.27	0.018
Folk	5.20	0.16	4.89	5.51	-15.69	< .001	-2.86	-2.23	0.001
Jazz	9.79	0.08	9.64	9.94	21.11	< .001	1.86	2.24	0.002
Latin	2.78	0.20	2.39	3.17	-25.21	< .001	-5.35	-4.58	0.003
New age	25.35	0.66	24.06	26.64	28.30	< .001	16.39	18.83	0.004
Pop	3.56	0.02	3.52	3.60	-61.17	< .001	-4.32	-4.05	0.020
Rap/ Hip hop	2.71	0.06	2.60	2.82	-60.43	< .001	-5.20	-4.87	0.019
Reggae/ Ska	1.98	0.34	1.31	2.64	-17.73	< .001	-6.41	-5.13	0.002
Rock	2.16	0.02	2.11	2.20	-80.65	< .001	-5.73	-5.45	0.034
Soul/ R&B	1.42	0.17	1.09	1.75	-36.85	< .001	-6.66	-5.99	0.007
Soundtracks	12.89	0.25	12.41	13.37	21.35	< .001	4.67	5.62	0.002
World	6.51	0.21	6.09	6.92	-5.87	< .001	-1.65	-0.83	0.000

Note. F (16, 143336) = 1617.47, p < .001, n_p^2 = .153. SE = Standard Error; CI = Confidence Interval.

Table 2b.

Means, Standard Errors, 95% Confidence Intervals, and Deviation Contrasts for the GLMM Analysis Concerning Genre Predicting Mood 2

					Deviation contrast: Genre compared to the mean				
Genre label	M	SE	95% CI		*t*	*p*	95% CI		η^2
Alternative/ Indie	8.21	0.24	7.75	8.68	-22.05	< .001	-5.75	-4.81	0.003
Children's	18.56	0.78	17.04	20.08	6.90	< .001	3.63	6.51	0.000
Christian/ Gospel	12.72	0.45	11.83	13.60	-1.79	.073	-1.63	0.07	0.000
Classical/ Opera	6.89	0.10	6.70	7.08	-51.74	< .001	-6.85	-6.35	0.014
Country	16.75	0.13	16.49	17.01	21.24	< .001	2.96	3.56	0.002
Electronica/Dance	7.67	0.05	7.56	7.77	-57.27	< .001	-6.03	-5.63	0.017
Folk	16.94	0.21	16.53	17.36	15.74	< .001	3.02	3.88	0.001
Jazz	13.84	0.10	13.64	14.04	2.64	.008	0.09	0.60	0.000
Latin	19.13	0.27	18.61	19.65	21.18	< .001	5.12	6.16	0.002
New age	7.42	0.89	5.68	9.17	-7.22	< .001	-7.72	-4.42	0.000
Pop	15.15	0.03	15.09	15.20	17.90	< .001	1.48	1.84	0.002
Rap/ Hip hop	11.85	0.07	11.70	11.99	-14.62	< .001	-1.87	-1.43	0.001
Reggae/ Ska	23.01	0.46	22.12	23.91	21.65	< .001	8.66	10.38	0.003
Rock	9.70	0.03	9.63	9.76	-40.53	< .001	-3.98	-3.61	0.009
Soul/ R&B	17.85	0.23	17.40	18.30	18.80	< .001	3.90	4.81	0.002
Soundtracks	7.27	0.33	6.62	7.93	-19.10	< .001	-6.86	-5.58	0.002
World	16.42	0.29	15.86	16.99	10.27	< .001	2.37	3.49	0.001

Note. F (16, 143335) = 2014.14, p < .001, n_p^2 = .184. SE = Standard Error; CI = Confidence Interval.

Table 2c.

Means, Standard Errors, 95% Confidence Intervals, and Deviation Contrasts for the GLMM Analysis Concerning Genre Predicting Mood 3

					Deviation contrast: Genre compared to the mean				
Genre label	M	SE	95% CI		*t*	*p*	95% CI		η^2
Alternative/ Indie	25.68	0.40	24.90	26.47	37.69	< .001	14.51	16.10	0.008
Children's	3.89	1.32	1.31	6.47	-5.20	< .001	-8.92	-4.04	0.000
Christian/ Gospel	8.12	0.77	6.62	9.62	-3.08	.002	-3.70	-0.82	0.000
Classical/ Opera	6.92	0.17	6.60	7.24	-15.97	< .001	-3.88	-3.03	0.001
Country	9.25	0.23	8.80	9.69	-4.34	< .001	-1.64	-0.62	0.000
Electronica/Dance	6.66	0.09	6.49	6.84	-21.52	< .001	-4.05	-3.38	0.002
Folk	9.65	0.36	8.94	10.36	-1.96	.050	-1.46	0.00	0.000
Jazz	4.14	0.17	3.80	4.48	-28.06	< .001	-6.67	-5.80	0.004
Latin	8.97	0.45	8.08	9.86	-3.11	.002	-2.29	-0.52	0.000
New age	4.21	1.51	1.25	7.17	-4.32	< .001	-8.96	-3.37	0.000
Pop	14.57	0.05	14.48	14.63	26.73	< .001	3.89	4.50	0.004
Rap/ Hip hop	5.21	0.13	4.97	5.46	-27.03	< .001	-5.54	-4.79	0.004
Reggae/ Ska	2.66	0.78	1.14	4.19	-10.35	< .001	-9.18	-6.25	0.001
Rock	33.74	0.05	33.63	33.85	147.04	< .001	23.05	23.68	0.104
Soul/ R&B	11.86	0.39	11.11	12.62	3.79	< .001	0.72	2.26	0.000
Soundtracks	12.16	0.57	11.05	13.27	3.23	.001	0.70	2.87	0.000
World	8.69	0.49	7.73	9.65	-3.49	< .001	-2.64	-0.74	0.000

Note. F (16, 143335) = 8190.39, p < .001, n_p^2 = .478. SE = Standard Error; CI = Confidence Interval.

Table 2d.

Means, Standard Errors, 95% Confidence Intervals, and Deviation Contrasts for the GLMM Analysis Concerning Genre Predicting Mood 4

					Deviation contrast: Genre compared to the mean				
Genre label	M	SE	95% CI		*t*	*p*	95% CI		η^2
Alternative/ Indie	8.48	0.22	8.04	8.91	-22.32	< .001	-5.48	-4.60	0.003
Children's	24.40	0.73	22.97	25.83	15.72	< .001	9.53	12.24	0.001
Christian/ Gospel	15.39	0.43	14.55	16.22	4.59	< .001	1.07	2.67	0.000
Classical/ Opera	12.19	0.09	12.01	12.37	-11.02	< .001	-1.56	-1.09	0.001
Country	13.50	0.13	13.25	13.75	-0.11	.916	-0.30	0.27	0.000
Electronica/Dance	10.27	0.05	10.17	10.37	-33.81	< .001	-3.43	-3.06	0.006
Folk	13.79	0.20	13.39	14.18	1.32	.187	-0.13	0.68	0.000
Jazz	23.33	0.10	23.14	23.52	79.51	< .001	9.58	10.06	0.033
Latin	13.36	0.25	12.87	13.85	-0.62	.535	-0.65	0.34	0.000
New age	12.00	0.84	10.36	13.65	-1.91	.056	-3.07	0.04	0.000
Pop	10.75	0.03	10.69	10.80	-31.74	< .001	-2.94	-2.60	0.005
Rap/ Hip hop	12.61	0.07	12.48	12.75	-8.50	< .001	-1.11	-0.69	0.000
Reggae/ Ska	14.95	0.43	14.10	15.80	3.46	.001	0.62	2.25	0.000
Rock	6.24	0.03	6.19	6.30	-82.30	< .001	-7.44	-7.10	0.035
Soul/ R&B	14.38	0.22	13.96	14.81	3.98	< .001	0.44	1.30	0.000
Soundtracks	7.14	0.32	6.52	7.76	-20.76	< .001	-6.98	-5.77	0.002
World	16.97	0.27	16.44	17.51	12.85	< .001	2.93	3.99	0.001

Note. F (16, 143335) = 2536.27, p < .001, n_p^2 = .221. SE = Standard Error; CI = Confidence Interval.

Table 2e.

Means, Standard Errors, 95% Confidence Intervals, and Deviation Contrasts for the GLMM Analysis Concerning Genre Predicting Mood 5

					Deviation contrast: Genre compared to the mean				
Genre label	M	SE	95% CI		*t*	*p*	95% CI		η^2
Alternative/ Indie	13.23	0.33	12.59	13.87	-5.49	< .001	-2.46	-1.17	0.000
Children's	15.00	1.07	12.90	17.10	-0.04	.967	-2.03	1.95	0.000
Christian/ Gospel	11.73	0.62	10.51	12.95	-5.54	< .001	-4.48	-2.14	0.000
Classical/ Opera	4.29	0.14	4.02	4.55	-61.08	< .001	-11.10	-10.41	0.020
Country	15.48	0.18	15.12	15.84	2.06	.040	0.02	0.85	0.000
Electronica/Dance	15.01	0.07	14.86	15.15	-0.25	.806	-0.31	0.24	0.000
Folk	16.59	0.30	16.01	17.17	5.12	< .001	0.96	2.14	0.000
Jazz	9.93	0.14	9.66	10.21	-28.27	< .001	-5.46	-4.76	0.004
Latin	23.50	0.37	22.78	24.22	23.02	< .001	7.74	9.18	0.003
New age	4.91	1.23	2.50	7.32	-8.73	< .001	-12.40	-7.86	0.000
Pop	19.98	0.04	19.90	20.05	38.67	< .001	4.69	5.19	0.008
Rap/ Hip hop	17.25	0.10	17.06	17.45	14.24	< .001	1.91	2.52	0.001
Reggae/ Ska	20.67	0.63	19.43	21.91	9.27	< .001	4.43	6.81	0.000
Rock	18.23	0.04	18.15	18.32	24.67	< .001	2.94	3.44	0.003
Soul/ R&B	25.23	0.32	24.61	25.84	31.83	< .001	9.56	10.81	0.005
Soundtracks	8.80	0.46	7.90	9.71	-13.88	< .001	-7.12	-5.36	0.001
World	15.89	0.40	15.11	16.67	2.15	.032	0.07	1.62	0.000

Note. F (16, 143335) = 1234.87, p < .001, n_p^2 = .121. SE = Standard Error; CI = Confidence Interval.

Table 2f.

Means, Standard Errors, 95% Confidence Intervals, and Deviation Contrasts for the GLMM Analysis Concerning Genre Predicting Mood 6

					Deviation contrast: Genre compared to the mean				
Genre label	M	SE	95% CI		*t*	*p*	95% CI		η^2
Alternative/ Indie	9.25	0.25	8.75	9.74	-7.92	< .001	-2.50	-1.51	0.000
Children's	14.60	0.82	12.99	16.21	4.31	< .001	1.82	4.87	0.000
Christian/ Gospel	15.77	0.48	14.83	16.71	9.86	< .001	3.62	5.42	0.001
Classical/ Opera	9.56	0.10	9.35	9.76	-12.56	< .001	-1.96	-1.43	0.001
Country	19.38	0.14	19.10	19.66	50.09	< .001	7.81	8.45	0.013
Electronica/Dance	2.79	0.06	2.68	2.90	-78.60	< .001	-8.68	-8.26	0.032
Folk	16.22	0.23	15.78	16.66	21.39	< .001	4.51	5.42	0.002
Jazz	18.44	0.11	18.28	18.65	51.84	< .001	6.92	7.46	0.014
Latin	10.12	0.28	9.56	10.67	-4.03	< .001	-1.69	-0.58	0.000
New age	15.77	0.94	13.93	17.62	5.08	< .001	2.77	6.26	0.000
Pop	9.78	0.03	9.73	9.84	-15.01	< .001	-1.66	-1.28	0.001
Rap/ Hip hop	3.72	0.08	3.57	3.87	-63.19	< .001	-7.77	-7.30	0.021
Reggae/ Ska	10.93	0.49	9.98	11.88	-0.69	0.488	-1.24	0.59	0.000
Rock	5.59	0.03	5.52	5.65	-57.14	< .001	-5.86	-5.47	0.017
Soul/ R&B	7.82	0.24	7.34	8.29	-14.00	< .001	-3.92	-2.96	0.001
Soundtracks	10.19	0.35	9.49	10.88	-3.10	0.002	-1.74	-0.39	0.000
World	11.39	0.31	10.79	11.99	0.46	0.647	-0.45	0.73	0.000

Note. F (16, 143335) = 2394.97, p < .001, n_p^2 = .211. SE = Standard Error; CI = Confidence Interval.