North, Adrian C., Krause, Amanda E., Sheridan, Lorraine P., and Ritchie, David (2020) ***Comparison of popular music in the United States and the United Kingdom: computerized analysis of 42,714 pieces.*** **Psychology of Music, . (In Press)**

http://doi.org/10.1177/0305735619830185

Note:

Published citation:

North, A. C., Krause, A. E., Sheridan, L. P., & Ritchie, D. (2019). Comparison of popular music in the United States and the United Kingdom: Computerised analysis of 42,714 pieces. *Psychology of Music,* advanced online publication*.* doi:10.1177/0305735619830185

Comparison of Popular Music in the United States and the United Kingdom: Computerised Analysis of 42,714 Pieces

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Abstract

The present research employed computerised analyses of all those pieces to have achieved any degree of commercial success in either the United States or the United Kingdom in terms of energy, beats per minutes, and several emotion scores. Analyses showed differences between these two commercially-complete musical cultures in all variables except one of the emotion scores; that the relationship between popularity and each of the remaining variables was similar across the two countries; but that there were differences in the representation of genres. These findings indicate that it is possible to identify quantitative differences between musical cultures, and may have implications for ethnomusicology and the nascent digital music streaming industry.

Keywords:

music, popularity, emotion, energy, culture

North and Hargreaves' (2008) review of the social psychology of music characterised the field as operating at four hierarchical levels. Drawing heavily on Doise's (1986) conceptualisation of social psychology in general, North and Hargreaves claimed that social processes in musical behaviour operate at intrapersonal, interpersonal, socio-positional, and ideological levels, with each of these representing an increasing level of social generality in turn. The past three decades have given rise to a growing amount of work at the three lower levels of this hierarchy, concerning respectively, for instance, work on intraindividual factors such as personality (e.g., North, 2010; Rentfrow & Gosling, 2003); factors that operate between individuals, such as interpersonal relationships (e.g., Wapnick, Darrow, Kovacs, & Dalrymple, 1997); and factors concerning relationships between social groups, such as conformity (e.g., Kuntsche, Mével, & Berson, 2016). However, limitations in computing power until recent years, among other factors, mean that only a small amount of previous work has considered music aesthetics at the highest, ideological level which concerns social processes at the level of an entire culture by reference to, for example, an entire musical corpus or at least very large samples (e.g., de Clercq & Temperley, 2011; Gauvin, 2015; Kreyer & Mukherjee, 2009). This work has mostly considered how music might have changed over time, and falls into two categories, namely, that which has focused on the music (e.g., tempo, mode, harmonics, chord transitions) and that which has focused on song lyrics.

With regard to research on music itself, by using tempo and mode as indicators of emotional cues, Schellenberg and von Scheve (2012) found that American popular music has become progressively more emotionally ambiguous and sad-sounding. Gauvin (2015) considered changes in pitch structure in American popular music from 1958-1971 and found that while there was no significant difference between the first and second half of the decade with regard to the use of modulation, there was an increase in the second half of the decade with regard to the use of flat-side harmonies. Several researchers (e.g., de Clercq &

Temperley, 2011; Temperley & de Clercq, 2013) have focused on rock music in particular. This work demonstrated patterns in pitch, melody, and harmony over time, such that major triads are more common than minor triads. Serra, Corral, Boguñá, Haro, and Arcos (2012) used the 'Million Song dataset' to investigate western popular music in terms of loudness, pitch, and timbre: they observed trends demonstrating "less variety in pitch transitions, towards a consistent homogeniation of the timbral palette, and towards louder" music (p. 5). Perhaps the best-known research of this nature was conducted by Dean Simonton during the 1980s (see review by Simonton, 1997). This found, for instance, that there is an inverted-J shaped relationship between measures of melodic originality and popularity among 15,618 classical music themes.

With regard to song lyrics, DeWall, Pond, Campbell, and Twenge (2011) examined song lyrics as cultural products. They demonstrated that references to self-focus and antisocial behaviour increased over time, whereas other-focus, social interaction, and positive emotional language decreased over time. Much of this work has considered the relationship between song lyrics and changes over time in various macro-level indicators of national economic performance. Zullow (1991), for instance, argued that the lyrics of top-selling pop songs should reflect national mood, and used this to explain the finding that pessimistic rumination in the lyrics should precede reductions in consumer optimism and subsequently Gross National Product. Similarly, Pettijohn and colleagues (e.g., Pettijohn II & Sacco Jr., 2009b) have argued that the nature of popular music reflects societal turbulence, so that socioeconomic threat leads to the popularity of music promoting maturity, certainty, and succour (see also Eastman & Pettijohn II, 2015; Pettijohn II & Sacco Jr., 2009a).

Unfortunately, however, although many of these studies consider bodies of music far larger than those seen in most research, the music studied is nonetheless limited as it usually comprises those songs that peaked on one particular chart (e.g., Billboard) within one given country, and only a certain number of 'representative songs' from each year (such as the ten highest-selling songs). There is very little work that has featured entire commercial musical cultures (which might be operationalised as all those recordings to have received a commercial release), and only one study has attempted a direct quantitative comparison of musical cultures. Achterberg, Heilbron, Houtman, and Aupers (2011) considered the globablization of top-selling music using information from American, Dutch, French, and German charts (1965-2006). By coding the performer nationality and language sung, they were able to consider the distribution of songs across the four countries. While they found no increase in the proportion of foreign music in national charts across time, the number of nationalities represented did increase over time, demonstrating increasing cultural diversification of the charts.

The scarcity of attempts to quantify the nature of differences or similarities between musical cultures has been noted on several occasions over recent years. Approaching music preference from an educational standpoint, Teo, Hargreaves, and Lee (2008) remarked that, "it would be reasonable to expect cross-cultural variations in the music behaviors … including music preferences" (p. 20) given the differences in educational systems. They continue to state that the previous research concerning cross-cultural musical preference has focused on the importance of music in different cultures. Indeed, cross-cultural studies have typically compared responses to Western and non-Western music by people from Western and non-Western countries (Teo et al., 2008; see for example: Egermann, Fernando, Chuen, & McAdams, 2015; Fritz, Schmude, Jentschke, Friederici, & Koelsch, 2013). However, while culture-specific listening profiles are typically found, emotional interpretation of music can to some extent transcend cultural boundaries: in Fritz, et al.'s (2013) study, for instance, Mafa listeners could to some extent decode iconic meaning in Western music; and there were similarities to the Canadian and remote Congolese listeners' responses regarding emotion and arousal in Egermann, et al.'s (2015) study.

However, with the exception of the research by Achterberg et al. (2011), we are not aware of any other findings that have attempted a quantitative comparison between two cultures of all the music from within each to have achieved commercial success. The present research aims to compare the psychological variables that correlate with popularity in two complete commercial musical cultures, namely the United States and United Kingdom. These two were selected on the basis of being large markets that have produced music to have enjoyed arguably an international reach. Previous research (North, Krause, Sheridan, & Ritchie, 2017, 2018a, 2018b) has used datasets from each country representing all those pieces to have enjoyed any degree of commercial success. This earlier work showed that popularity within country can be predicted on the basis of scores for each piece concerning energy and various different emotions, although the nature of these relationships provided only very limited support for some established theories of music aesthetics. Moreover, although North et al. (2018b) included some limited verbal content that compared the nature of these relationships between the US and UK, there is the clear opportunity to carry out a quantitative comparison that explicitly compares the two sets of data. Energy was employed as a proxy for the dimension of arousal that has received so much attention in psychological research concerning music aesthetics: for example, arguably the best-known aspect of Berlyne's (1971) work is that arousal is the key driver of musical (and other artistic) likes and dislikes, such that there is an inverted-U relationship between the two in which moderately-arousing music should be most popular. Different researchers have operationalised arousal in different ways across a number of studies conducted since the 1960s (see review by North & Hargreaves, 2008): these have included the complexity (Heyduk, 1975), information content (Vitz, 1966), familiarity (see Hargreaves, 1986), timbre (Konečni, 1982), or tempo (North &

Hargreaves, 2000) of the music. Common to all these, however, is a sense of the degree of energy and activity present within or evoked by the music, and it is unsurprising that humans' ratings of these factors correlate positively (e.g., Marin, Lampatz, Wandl, & Leder, 2016). Similarly a large amount of research on emotion (i.e., short-term responses to a stimulus, as distinct from longer-term moods) has considered these in terms of the circumplex model (see Russell, 1978). This model asserts that any given emotion can be understood in terms of its position along two orthogonal dimensions, namely pleasant-unpleasant and active-sleepy, and a number of studies have applied this successfully to music (e.g., Kreutz, Ott, Teichmann, Osawa, & Vaitl, 2008; North & Hargraves, 1997; Ritossa & Rickard, 2004). Of course, emotion is also the most apparent psychological response to music (see Garrido, 2014; Sloboda & Juslin, 2001).

The most important aspect of research on both the circumplex model and Berlyne's account of musical preference, however, is that they claim to explain emotions and musical preferences across listeners, cultures, and genres. Berlyne's approach is based on the effect of music (or other artistic stimuli) on the ascending reticular activating system (although this is clearly controversial – see, e.g., Martindale, 2007), such that the same relationship between aesthetic response and arousal should be expected cross-culturally. However, there have been very few attempts to directly test Berlyne's theory cross-culturally or among non-western samples (e.g., Berlyne, 1975). Similarly, the validity of the circumplex model has been explicitly demonstrated in a number of different cultures (e.g., Furrer, Tjemkes, Aydinlik, & Adolfs, 2012; Russell, 1983; Russell, Lewicka, & Niit, 1989). We might therefore expect to find that energy and emotion are related to music in similar ways cross-culturally.

The findings reported here directly compare all those musical pieces to have achieved any degree of success on British and American singles charts against one another to identify any differences in energy and emotion scores, and the relationship between these and the popularity of the pieces. Given the limited amount of previous research it is difficult to hypothesise with confidence. However, on an exploratory basis at least, the first hypothesis was that the status of music as a cultural product implies clearly that pieces that have been popular in the United States may differ from those that have been popular in the United Kingdom in terms of energy and emotion scores: if what is popular in one culture differs from what is popular in another then it is reasonable to expect differences between those two sets of music in terms of both their actual energy and emotion scores. However, the second exploratory hypothesis was that the two countries may nonetheless give rise to similar *relationships* between popularity and both energy and emotion scores assigned to the music. Such findings would indicate that quantitative differences exist between the United States' and United Kingdom's commercial musical cultures, but that these share a common theoretical basis.

Method

The research used the same core dataset and approach to analyzing the music as several existing papers, namely, North, Krause, Sheridan, and Ritchie (2017, 2018a, 2018b) .

Dataset

The research employed a master dataset created by the music industry for use by radio stations and the like, based on data from over 400,000 record companies. This information can be obtained directly from record labels, although at the time of writing there are also a number of commercial aggregation services that licence access (such as 7 Digital, Medianet, and Soundcloud). It contains over 38 million pieces, and represents the canonical list of all commercially-released music in Europe, North America, and Australasia. The classification of pieces into genres is carried out by the record company of the artist in question, and takes place at the level of the artist so that all works by a given artist are classed into a single genre. The selection of the genre is made from 23 candidates (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). Created on 10 May 2016, the subset of this master dataset used in the present research contained 42,714 pieces of music: these were selected as all and only those to have appeared on singles sales and/or radio airplay charts in the United Kingdom and the United States of America, and which had therefore enjoyed any commercial success whatsoever in at least one of those two countries.

Energy. The energy value for each piece was calculated via an algorithmic artificial intelligence process that used bespoke-architected chip sets. The means by which this is and the calculation of other variables is carried out is detailed in U.S. Patent No. 7,081,579 B2 (2006), U.S. Patent No. 2010/0250471 (2010), and U.S. Patent No. 2008/0021851 (2008) to which interested readers should refer. Briefly, these patents outline a machine learning algorithm that identifies examples of musical pieces that are similar to one another, which can be determined on the basis of any number of constructs and combinations thereof, including mood and energy. The sonic characteristics analyzed include factors such as melody, tempo, rhythm, brightness, octave, and low frequency, although it is the combination of these characteristics rather than the individual characteristics that is important (U.S. Patent No. 7,081,579 B2, 2006). Within the U.S. Patent No. 2008/0021851 (2008; see also U.S. Patent No. 2010/0250471, 2010), the processes for identifying "examples of similar songs" (p. 7) pertains to the energy score specifically. In calculating energy scores, the AI was trained via a set 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. The AI process used 69 differing combinations of 11 sonic properties (e.g., tempo, beat, pitch, and rhythm) of the pieces to learn how to distinguish calm and energetic music. Within each of the sets of exemplar tracks, each individual piece was compared against the 99 others, and if the majority of the 10 most acoustically-similar tracks were from the same class as the exemplar track then the latter was regarded as having been classified appropriately. Within the initial batch of training tracks, 182 were classified correctly, and subsequent iterations replaced the 18 other tracks until 100% accuracy had been achieved. The computer then proceeded to assign an energy score to every track in the complete database on the basis of the extent of the acoustic similarity between each and the remainder, so that more similar tracks had more similar energy ratings assigned to them. The face validity of these ratings was then assessed informally by the researchers via a quasi-random sample of 1000 tracks representing the range of energy scores.

Beats per minute (BPM). Five algorithmic measures of beats per minute (BPM) were tested on the basis of the industry-standard open source C++ library developed by the Music Technology Group of Pompeu Fabra University (http://essentia.upf.edu). The values produced by each of the five on a sub-sample of tracks were compared against human ratings and the two best-performing by this criterion were combined and used in the present research. The "Beat Tracker" algorithm is based on autocorrelations values and calculates BPM in chunks (U.S. Patent No. 7,081,579 B2, 2006). For each track, BPM measurements were taken every 30 seconds and subsequently averaged to produce a single value per track. The face validity of these values was then assessed informally as per energy scores.

Hit popularity. Popularity is based on the commercial success of the music in the database, including common industry indicators such as total sales, highest chart position, and date of release (U.S. Patent No. 7,081,579 B2, 2006). In particular, the commercial success of each piece was assessed via 74 sales and/or radio airplay charts from the United Kingdom and United States. The popularity measure employed regional and national charts, albums and singles charts, and genre-specific in addition to 'overall' charts. Examples of these include the Billboard hot 100, the Billboard blues album chart, the Billboard jazz songs chart, the Billboard Christian album chart, the Billboard country airplay chart, the Billboard bluegrass albums chart, the UK singles chart, the UK dance music albums chart, the UK rock and metal singles chart, the UK classical albums chart, and the UK indie singles chart. Within each country, a weighting was assigned to each chart so that national charts received a greater weighting and regional charts were weighted according to the size of the region in question, singles charts were weighted higher than albums charts (as the former represent a more direct test of the popularity of the specific song in question), and overall charts were assigned a greater weighting than were genre-specific charts, which were weighted according to the size of the market. For example, the United Kingdom singles chart was assigned a weighting of 1; the corresponding albums charts were assigned a weighting of .5 (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. Moreover, based on the popularity scores, each track was also coded such that it was allocated to one of three distinct groups. Any track with a popularity value in one country but not the other was allocated to that particular country (i.e., labeled as belonging to either the US or the UK respectively), whereas tracks with popularity values for both the US and the UK (e.g., tracks that were popular in both countries) were allocated to a separate, third category.

Emotion scores. Each track was assigned a score on each of seven emotions, which were selected at the time the master database was established on grounds of commercial relevance to the music industry (particularly to music radio programming) rather than any theoretical concerns. Although selected on commercial rather than theoretical grounds (so that they do not necessarily reflect the outcomes of previous research on music and emotion), these emotions have face validity as common responses to music. The emotions were emotion 1 = clean, simple, relaxing, emotion 2 = happy, hopeful, ambition, emotion 3 = passion, romance, power, emotion 4 = mystery, luxury, comfort, emotion 5 = energetic, bold, outgoing, emotion 6 = calm, peace, tranquility, and emotion 7 = sad respectively. Calculation of the emotion scores for each track followed a similar process to that employed for energy. Six musicians and sound engineers assigned emotion ratings to 300 seed tracks that were believed to provide a good range of scores across the emotions, and these formed the basis of an AI training process (detailed in U.S. Patent No. 2010/0250471, 2010; U.S. Patent No. 2008/0021851, 2008; U.S. Patent No. 7,081,579 B2, 2006). The computer analyzed each piece according to 69 algorithmic combinations of 11 sonic characteristics (as per energy). Then the computer assessed the similarity of each individual track to the remainder according to these same factors, and then assigned emotion scores so that more similar pieces were assigned more similar emotion scores. The face validity of the resulting values was then assessed informally as per energy scores.

Results and discussion

The dataset used included a total of 42,714 tracks that had some degree of popularity in either the UK or US singles charts (i.e., a popularity score greater than 0). Of these 42,714 tracks, 6,368 tracks had a positive score for *both* the UK *and* US, while 18,680 had a US popularity score only, and 17,666 tracks had a UK popularity score only. Summary data concerning these tracks is presented in Table 1. Unsurprisingly, the analysis concerning the tracks with a positive popularity score in *both* the UK *and* the US gave rise to a positive correlation, $\tau = .221$, $p < .001$, two-tailed, $N = 6{,}368$.

Due to violations of normality in the data, a series of Mann-Whitney U tests ($\alpha = .001$) was performed to compare tracks that had *only* a UK popularity score against those which had *only* a US popularity score in terms of each variable (i.e., excluding the 6,358 tracks with both US *and* UK popularity scores). As illustrated in Table 2, all the variables except for emotion 3 (passion, romance, power) differed between tracks that were popular in the UK and US respectively: mean ranks indicated that tracks popular in the US scored higher (i.e., lower mean ranks) than tracks popular in the UK on measures of energy, BPM, emotion 1 (clean, simple, relaxing), and emotion 4 (energetic, bold, outgoing); whereas tracks popular in the UK scored higher (i.e., lower mean ranks) than tracks popular in the US on measures of emotion 2 (happy, hopeful, ambition), emotion 4 (mystery, luxury, comfort), emotion 6 (calm, peace, tranquility), and emotion 7 (sad). As such, these results support the first hypothesis, and specify quantitatively how these two commercial musical cultures differ from one another, and that these differences were wide-ranging.

- Table 1 and 2 here -

In order to consider those aspects of tracks most predictive of popularity within the UK and US respectively, two Generalized Linear Mixed Model (GLMM) analyses were performed ($\alpha < .001$). Energy, BPM, and the seven emotion scores served as predictor variables in two separate GLMM analyses concerning the UK popularity score and US popularity score respectively (again using only those tracks with a popularity value in only one country). As shown in Table 3, both GLMM overall models were statistically significant.

- Table 3 here -

Although the effect sizes arising from these analyses were very small, it is also noteworthy that the popularity data are subject to considerable external influence such as radio airplay and other music industry marketing as well as a panoply of other factors. As such, it is interesting that relationships can be nonetheless identified between popularity and each of the variables concerning the music per se. Table 3 shows that popularity in the UK was related positively to BPM and negatively to emotion 2 (happy, hopeful, ambition), emotion 3 (passion, romance, power), emotion 5 (energetic, bold, outgoing), emotion 6 (calm, peace, tranquility), and emotion 7 (sad): popularity in the US was related negatively to emotion 1 (clean, simple, relaxing), emotion 2 (happy, hopeful, ambition), emotion 3 (passion, romance, power), emotion 4 (mystery, luxury, comfort), emotion 5 (energetic, bold, outgoing), and emotion 6 (calm, peace, tranquility). As this indicates, the only differences between the UK and US were in terms of BPM and emotion 1 (clean, simple, relaxing), so that when considering the remaining emotions, those that are characteristic of commercial success in the UK are also characteristic of commercial success in the US. As such this appears consistent with the second exploratory hypothesis. Note also that the negative relationships between popularity and emotion scores indicate that the former is associated with music that is arguably emotionally-bland.

More formally, Table 3 indicates that ‘popular music’ in the United States has the same emotion as ‘popular’ music in the United Kingdom but, given that the tracks in question achieved popularity only in *either* the US *or* the UK, it appears that these emotions are realized by different sets of songs. To test further the notion that the two countries use different music to achieve apparently similar emotional ends, a chi-square test considered the degree of association between the country in which each track was popular and the genre represented by each track. The result of this analysis (which employed tracks that had *either* a UK or US popularity score) was significant, χ^2 (22, N = 36,345) = 9393.09, p < .001, ϕ = .508. Table 4 shows the distribution of genres between countries, and indicates that certain genres (e.g., Christian/gospel, country, Latin, soul/R&B) were more likely to feature in the list of tracks that had achieved popularity in the United States, whereas other genres (e.g., electronic/dance, reggae/ska) were more likely to feature in the list of tracks that had achieved popularity in the United Kingdom. This seems to provide support for the contention that although both markets place commercial value on the same emotions in music they do so via different stylistic conventions, such as instrumentation, subject matter, and any of a number of other variables that constitute a 'genre'.

- Table 4 here –

In conclusion, the present findings quantify the nature of the differences between all music that has achieved any degree of popularity in the United States and United Kingdom. The two sets of music differ from one another, and represent differing genres, although the relationship between popularity and emotion in each country is very similar. Findings such as these demonstrate the differences and similarities between two notable commercial musical cultures.

Nonetheless, the present findings are of course limited by a number of factors. First, they are of course limited to those variables analysed by the AI, namely energy and emotion, and future work will of course be required to validate the present findings and extend them to a range of other variables. Second, the classification of music into genres can be carried out in a number of ways (see, e.g., Nattiez's [1990] detailed account), and differing classification methods to that employed here have the potential to produce different results.

The present results also serve as a basis for at least six other lines of future work that address either other limitations of the work or new opportunities that arise from it. First, the present findings provide a working method for quantifying differences between any commercial musical cultures, so that these can be understood precisely. As such, they may make a useful contribution to the ethnomusicological literature. Second, it may be possible to explain the findings reported in Table 4, concerning genre preferences by country, in the light of either the relative prominence of cultural sub-groups within the national population in question, or in terms of quantitative approaches to culture in general. For instance, Hofstede's (e.g., 1980) well-known quantitative dimensional model of culture may map onto differences in commercial musical cultures, so that, for example, the popularity of music with high energy scores may be more prevalent among those cultures that score highly on Hofstede's 'masculinity' dimension of national culture. It is notable in this context that Juslin, Barradas, Ovsiannikow, Limmo, and Thompson (2016) reported some differences in emotional reactions to music between individualistic and collectivistic cultures, such that Hofstede's other dimensions may be relevant also.

Third, the present results have potential practical value. As the music industry moves towards internet-based streaming in which a small number of companies serve music to a number of different nations via a subscription model, so it becomes increasingly important to understand how music markets differ between countries. Quantifying these differences will allow companies to adjust their recommendation algorithms between nations in order to maximize customer satisfaction and the maintenance of subscription payments. Fourth, as with any artificial intelligence process, the outputs (i.e., in this case, the scores assigned to the music) are contingent upon the training process. In the present case, this training was carried out by people with a strong interest in and knowledge of music, although whether different scores would result from a training process that employs members of the general public remains moot.

Fifth, the analyses were conducted between tracks that were popular either in the UK or the US, and so excluded those tracks that enjoy a high level of popularity in both countries: future research might investigate whether the latter group of tracks differ in some way from those that attain popularity in predominantly one country only. Sixth, the database employed here places relatively little emphasis on negatively-valenced emotions or the outcomes of some of the notable previous research on music and emotion, and clearly it would be interesting to incorporate these factors into the existing set of music. We should note also, however, that this would require a very significant investment in computer time. Seventh, the United States and United Kingdom are culturally similar, and so it may be interesting for future research to compare more disparate cultures via the same approach here.

Finally, as noted earlier, there is a scarcity of research that attempts to carry out a quantitative cross-cultural comparison of large bodies of music. For example, there are instances cited above of research that has considered changes over time within large samples of music that are drawn from within a single culture, but which do not explicitly compare cultures. The present findings suggest that any conclusions reached within a given commercial musical culture should not be extrapolated to others. Similarly, other previous work cited above has identified similarities and differences in responses to smaller samples of music drawn from several cultures, and the present findings perhaps give some indication that work of this nature could be carried out using machine learning concerning much larger samples of music.

References

Achterberg, P., Heilbron, J., Houtman, D., & Aupers, S. (2011). A cultural globalization of popular music? American, Dutch, French, and German popular music charts (1965 to 2006). *American Behavioral Scientist, 55*(5), 589-608. doi:10.1177/0002764211398081

Alcalde, V., Ricard, J., Bonet, A., Llopis, A., & Marcos, J. (2008). U.S. Patent No. 2008/0021851. Washington, DC: U.S. Patent and Trademark Office.

Alcalde, V., Ricard, J., Bonet, A., Llopis, A., & Marcos, J. (2010). U.S. Patent No. 2010/0250471. Washington, DC: U.S. Patent and Trademark Office.

Alcalde, V., Ullod, C., Bonet, A., Llopis, A., Marcos, J., Ysern, D., & Arkwright, D. (2006). U.S. Patent No. 7,081,579 B2. Washington, DC: U.S. Patent and Trademark Office.

Berlyne, D. E. (1971). *Aesthetics and psychobiology*. New York, NY: Appleton-Century-Crofts.

Berlyne, D. E. (1975). Extension to Indian subjects of exploratory and verbal responses to visual patterns. *Journal of Cross-Cultural Psychology, 6*(3), 316-330.

de Clercq, T., & Temperley, D. (2011). A corpus analysis of rock harmony. *Popular Music, 30*(1), 47-70. doi:10.1017/S026114301000067X

DeWall, C. N., Pond, R. S. J., Campbell, W. K., & Twenge, J. M. (2011). Tuning in to psychological change: Linguistic markers of psychological traits and emotion over time in popular U.S. song lyrics. *Psychology of Aesthetics, Creativity, and the Arts, 5*(3), 200-207. doi:10.1037/a0023195

Doise, W. (1986). *Levels of explanation in social psychology*. Cambridge, UK: Cambridge University Press.

Eastman, J. T., & Pettijohn II, T. F. (2015). Gone country: An investigation of Billboard country songs of the year across social and economic conditions in the United States. *Psychology of Popular Media Culture, 4*(2), 155-171. doi:10.1037/ppm0000019

Egermann, H., Fernando, N., Chuen, L., & McAdams, S. (2015). Music induces universal emotion-related psychophysiological responses: Comparing Canadian listeners to Congolese Pygmies. *Frontiers in Psychology, 5*, : 1341. doi:10.3389/fpsyg.2014.01341

Fritz, T. H., Schmude, P., Jentschke, S., Friederici, A. D., & Koelsch, S. (2013). From understanding to appreciating music cross-culturally. *PLoS ONE, 8*(9), : e72500. doi:10.1371/journal.pone.0072500

Furrer, O., Tjemkes, B. V., Aydinlik, A. U., & Adolfs, K. (2012). Responding to adverse situations within exchange relationships: The cross-cultural validity of a circumplex model. *Journal of Cross-Cultural Psychology, 43*, 943-966. doi:10.1177/0022022111415671

Garrido, S. (2014). A systematic review of the studies measuring mood and emotion in response to music. *Psychomusicology: Music, Mind, and Brain, 24*(4), 316-327. doi:10.1037/pmu0000072

Gauvin, H. L. (2015). “The times they were a-changin’”: A database-driven approach to the evolution of harmonic syntax in popular music from the 1960s. *Empirical Musicology Review, 10*(3), 215-238.

Hargreaves, D. J. (1986). *The developmental psychology of music*. Cambridge: Cambridge University Press.

Heyduk, R. G. (1975). Rated preference for music composition as it relates to complexity and exposure frequency. *Perception and Psychophysics, 17*(1), 84-91.

Hofstede, G. (1980). *Culture’s consequences: international differences in work-related values*. Beverley Hills, CA: Sage.

Juslin, P. N., Barradas, G. T., Ovsiannikow, M., Limmo, J., & Thompson, W. F. (2016). Prevalence of emotions, mechanisms, and motives in music listening: A comparison of individualist and collectivist cultures. *Psychomusicology, 26*(4), 293–326. doi:10.1037/pmu0000161

Konečni, V. (1982). Social interaction and music preference. In D. Deutsch (Ed.), *The psychology of music* (pp. 497-516). New York, NY: Academic Press.

Kreutz, G., Ott, U., Teichmann, D., Osawa, P., & Vaitl, D. (2008). Using music to induce emotions: Influences of musical preference and absorption. *Psychology of Music, 36*(1), 101-126. doi:10.1177/0305735607082623

Kreyer, R., & Mukherjee, J. (2009). The style of pop song lyrics: A corpus-linguistic pilot study. *Anglia - Zeitschrift für englische Philologie, 125*(1), 31-58. doi:10.1515/ANGL.2007.31

Kuntsche, E., Mével, L. L., & Berson, I. (2016). Development of the four-dimensional Motives for Listening to Music Questionnaire (MLMQ) and associations with health and social issues among adolescents. *Psychology of Music, 44*(2), 219-233. doi:10.1177/0305735614562635

Marin, M. M., Lampatz, A., Wandl, M., & Leder, H. (2016). Berlyne revisited: Evidence for the multifaceted nature of hedonic tone in the appreciation of paintings and music. *Frontiers in Human Neuroscience, 10*, : 536. doi:10.3519/fnhum.2015.00536

Martindale, C. (2007). Recent trends in the psychology of aesthetics, art, and creativity. *Empirical Studies of The Arts, 25*(2), 121-141. doi:10.2190/B637-1041-2635-16NN

Nattiez, J.-J. (1990). *Music and discourse: Toward a semiology of music* (C. Abbate, Trans.). Princeton, NJ: Princeton University Press.

North, A. C. (2010). Individual differences in musical taste. *The American Journal of Psychology, 123*(2), 199-208. doi:10.5406/amerjpsyc.123.2.0199

North, A. C., & Hargraves, D., J. (1997). Liking, arousal potential, and the emotions expressed by music. *Scandinavian Journal of Psychology, 38*, 45-53. doi:10.1111/1467-9450.00008

North, A. C., & Hargreaves, D. J. (2000). Musical preferences during and after relaxation and exercise. *American Journal of Psychology, 113*(1), 43-67.

North, A. C., & Hargreaves, D. J. (2008). *The social and applied psychology of music*. Oxford, UK: Oxford University Press.

North, A. C., Krause, A. E., Sheridan, L. P., & Ritchie, D. (2017). Energy, typicality, and music sales: A computerized analysis of 143,353 pieces. *Empirical Studies of The Arts, 35*(2), 214-229. doi:10.1177/0276237416688063

North, A. C., Krause, A. E., Sheridan, L. P., & Ritchie, D. (2018a). Energy, popularity, and the circumplex: A computerized analysis of emotion in 143,353 musical pieces. *Empirical Studies of The Arts, 36*(2), 127-161. doi:10.1177/0276237417704339

North, A. C., Krause, A. E., Sheridan, L. P., & Ritchie, D. (2018b). Popularity, mood, energy, and typicality in music: A computerised analysis of 204,506 pieces. *Psychology of Aesthetics, Creativity, and the Arts, Advance online publication*. doi:10.1037/aca0000165

Pettijohn II, T. F., & Sacco Jr., D. F. (2009a). The language of lyrics: An analysis of popular billboard songs across conditions of social and economic threat. *Journal of Language and Social Psychology, 28*(3), 297-311. doi:10.1177/0261927X09335259

Pettijohn II, T. F., & Sacco Jr., D. F. (2009b). Tough times, meaningful music, mature performers: Popular Billboard songs and performer preferences across social and economic conditions in the USA. *Psychology of Music, 37*(2), 155-179.

Rentfrow, P. J., & Gosling, S. D. (2003). The do re mi's of everyday life: The structure and personality correlates of music preferences. *Journal of Personality and Social Psychology, 84*(6), 1236-1256. doi:10.1037/0022-3514.84.6.1236

Ritossa, D. A., & Rickard, N. S. (2004). The relative utility of 'pleasantness and liking' dimensions in predicting the emotions expressed by music. *Psychology of Music, 32*(1), 5-22. doi:10.117/0305735604039281

Russell, J. A. (1978). Evidence of convergent validity on the dimensions of affect. *Journal of Personality and Social Psychology, 36*, 1152-1168.

Russell, J. A. (1983). Pancultural aspects of the human conceptual organization of emotions. *Journal of Personality and Social Psychology, 45*(6), 1281-1288.

Russell, J. A., Lewicka, M., & Niit, T. (1989). A cross-cultural study of a circumplex model of affect. *Journal of Personality and Social Psychology, 57*, 848-856.

Schellenberg, E. G., & von Scheve, C. (2012). Emotional cues in American popular music: Five decades of the Top 40. *Psychology of Aesthetics, Creativity, and the Arts, 6*(3), 196-203. doi:10.1037/a0028024

Serra, J., Corral, Á., Boguñá, M., Haro, M., & Arcos, J. U. (2012). Measuring the evolution of contemporary western popular music. *Nature: Scientific Reports, 2*(521), 1-6. doi:10.1038/srep00521

Simonton, D. K. (1997). Products, persons, and periods: Historiometric analyses of compositional creativity. In D. J. Hargreaves & A. C. North (Eds.), *The social psychology of music* (pp. 107-122). Oxford, UK: Oxford University Press.

Sloboda, J. A., & Juslin, P. N. (2001). Psychological perspectives on music and emotion. In P. N. Juslin & J. A. Sloboda (Eds.), *Music and emotion* (pp. 71-104). Oxford, UK: Oxford University Press.

Temperley, D., & de Clercq, T. (2013). Statistical analysis of harmony and melody in rock music. *Journal of New Music Research, 2*(3), 187-204. doi:10.1080/09298215.2013.788039

Teo, T., Hargreaves, D. J., & Lee, J. (2008). Musical preference, identification, and familiarity: A multicultural comparison of secondary students from Singapore and the United Kingdom. *Journal of Research in Music Education, 56*(1), 18-32.

Vitz, P. C. (1966). Affect as a function of stimulus variation. *Journal of Experimental Psychology, 71*, 74-79.

Wapnick, J., Darrow, A.-A., Kovacs, J., & Dalrymple, L. (1997). Effects of physical attractiveness on evaluation of vocal performance. *Journal of Research in Music Education, 45*, 470-479.

Zullow, H. M. (1991). Pessimistic rumination in popular songs and newsmagazines predict economic recession via decreased consumer optimism and spending. *Journal of Economic Psychology, 12*, 501-526.

Table 1.

Summary of the data

Sample	Energy			BPM			Clean, simple, relaxing			Happy, hopeful, ambition			Passion, Romance, power		
	M	*Mdn*	*SD*	*M*	*Mdn*	*SD*	*M*	*Mdn*	*SD*	*M*	*Mdn*	*SD*	*M*	*Mdn*	*SD*
Full sample (N = 42,714)	80.863	72.102	52.110	72.894	60.199	48.857	3.771	2.350	5.177	14.801	13.910	7.827	17.822	14.250	14.821
Tracks with US popularity scores only (N = 18,680)	72.535	60.852	50.506	70.104	57.513	48.136	3.789	2.290	5.143	15.817	15.200	7.670	17.531	14.320	14.335
Tracks with UK popularity scores only (N = 17666)	89.224	81.307	52.898	75.818	63.120	50.141	3.919	2.490	5.442	13.591	12.180	7.827	17.986	13.880	15.364
Tracks with US and UK popularity scores (N = 6,368)	82.099	73.125	50.703	72.966	60.548	46.840	3.305	2.100	4.446	15.178	14.480	7.826	18.220	15.035	14.672

(Table Continued)

Sample	Mystery, luxury, comfort			Energetic, bold, outgoing			Calm, peace, tranquility			Sad song score		
	M	*Mdn*	*SD*	*M*	*Mdn*	*SD*	*M*	*Mdn*	*SD*	*M*	*Mdn*	*SD*
Full sample (N = 42,714)	11.570	9.980	8.064	19.316	18.200	9.982	9.443	6.710	8.652	40.010	35.600	20.983
Tracks with US popularity scores only (N = 18,680)	12.247	10.620	8.310	18.949	17.880	9.852	10.736	8.290	8.801	43.084	39.915	20.718
Tracks with UK popularity scores only (N = 17666)	10.985	9.460	7.799	19.384	18.250	10.171	8.401	5.460	8.641	37.159	31.665	21.104
Tracks with US and UK popularity scores (N = 6,368)	11.204	9.615	7.900	20.205	19.020	9.770	8.538	6.270	7.686	38.904	34.715	20.175

Table 2.
Results of the Mann-Whitney U Tests (N = 36,346).

Variable	Mann-Whitney U	Z	Asymp. Sig. (2-tailed)	US mean rank	UK mean rank
Energy	134673569.5	-30.334	< .001	16550.01	19890.18
BPM	153612665.5	-11.397	< .001	17563.88	18818.12
Mood 1: Clean, simple relaxing	160825320.5	-4.198	< .001	17949.99	18409.84
Mood 2: Happy, hopeful, ambition	135450337.5	-29.557	< .001	19755.41	16500.79
Mood 3: Passion, romance, power	164988856.5	-0.012	.991	18172.88	18174.16
Mood 4: Mystery, luxury, comfort	149323678.5	-15.680	< .001	19012.73	17286.10
Mood 5: Energetic, bold, outgoing	161060888.5	-3.940	< .001	17962.60	18396.50
Mood 6: Calm, peace, tranquility	130483709.0	-34.525	< .001	20021.29	16219.65
Mood 7: Sad	134568901.5	-30.438	< .001	19802.60	16450.90

Note. US N = 18680, UK N = 17666.

Table 3.
GLMM Analyses Predicting Popularity Scores

	F	*p*	β	t	95% CI		η^2
	UK Popularity [a]						
Energy	2.232	.135	0.000	-1.494	0.000	0.000	0.000
BPM	4.215	.040	0.000	2.053	0.000	0.000	0.000
Clean, simple, relaxing	3.357	.067	0.001	1.832	0.000	0.001	0.000
Happy, hopeful, ambition	53.800	< .001	-0.002	-7.335	-0.002	-0.001	0.003
Passion, Romance, power	87.256	< .001	-0.001	-9.341	-0.002	-0.001	0.005
Mystery, luxury, comfort	1.842	.175	0.000	-1.357	-0.001	0.000	0.000
Energetic, bold, outgoing	108.004	< .001	-0.003	-10.393	-0.003	-0.002	0.006
Calm, peace, tranquillity	27.037	< .001	-0.001	-5.200	-0.002	-0.001	0.002
Sad song score	77.378	< .001	-0.001	-8.796	-0.002	-0.001	0.004
	US Popularity [b]						
Energy	1.851	.174	0.000	1.361	0.000	0.000	0.000
BPM	2.835	.092	0.000	-1.684	0.000	0.000	0.000
Clean, simple, relaxing	14.348	< .001	-0.001	-3.788	0.001	0.000	0.001
Happy, hopeful, ambition	23.990	< .001	-0.001	-4.898	-0.002	-0.001	0.001
Passion, Romance, power	21.158	< .001	-0.001	-4.600	-0.001	-0.001	0.001
Mystery, luxury, comfort	11.146	.001	-0.001	-3.339	-0.001	0.000	0.001
Energetic, bold, outgoing	16.201	< .001	-0.001	-4.025	-0.002	-0.001	0.001
Calm, peace, tranquillity	25.047	< .001	-0.001	-5.005	-0.001	-0.001	0.001
Sad song score	2.891	.089	0.000	-1.700	-0.001	0.000	0.000

[a] Corrected model: N = 17666; $F(9, 17656) = 34.966$, $p < .001$, $n_p^2 = .018$. Degrees of freedom for each individual predictor variable = 1, 17656.

[b] Corrected model: N = 18680; $F(9, 18670) = 30.440$, $p < .001$, $n_p^2 = .014$. Degrees of freedom for each individual predictor variable = 1, 18670.

Note. CI = confidence interval.

Table 4.
Chi-square Analysis Results (N = 36,345)

Genre		Country US	Country UK	Total
Alternative/Indie	Count	659	1761	2420
	% within Genre	27.20%	72.80%	100.00%
	% within Country	3.50%	10.00%	6.70%
	% of Total	1.80%	4.80%	6.70%
Blues	Count	180	51	231
	% within Genre	77.90%	22.10%	100.00%
	% within Country	1.00%	0.30%	0.60%
	% of Total	0.50%	0.10%	0.60%
Cast	Count	1	12	13
	% within Genre	7.70%	92.30%	100.00%
	% within Country	0.00%	0.10%	0.00%
	% of Total	0.00%	0.00%	0.00%
Children's	Count	4	21	25
	% within Genre	16.00%	84.00%	100.00%
	% within Country	0.00%	0.10%	0.10%
	% of Total	0.00%	0.10%	0.10%
Christian/gospel	Count	778	29	807
	% within Genre	96.40%	3.60%	100.00%
	% within Country	4.20%	0.20%	2.20%
	% of Total	2.10%	0.10%	2.20%
Classical/opera	Count	37	80	117
	% within Genre	31.60%	68.40%	100.00%
	% within Country	0.20%	0.50%	0.30%
	% of Total	0.10%	0.20%	0.30%
Comedy/Spoken word	Count	30	20	50
	% within Genre	60.00%	40.00%	100.00%
	% within Country	0.20%	0.10%	0.10%
	% of Total	0.10%	0.10%	0.10%
Country	Count	2941	125	3066
	% within Genre	95.90%	4.10%	100.00%
	% within Country	15.70%	0.70%	8.40%
	% of Total	8.10%	0.30%	8.40%
Elect./Dance	Count	139	2328	2467
	% within Genre	5.60%	94.40%	100.00%
	% within Country	0.70%	13.20%	6.80%
	% of Total	0.40%	6.40%	6.80%
Folk	Count	135	115	250
	% within Genre	54.00%	46.00%	100.00%
	% within Country	0.70%	0.70%	0.70%
	% of Total	0.40%	0.30%	0.70%

Instrumental	Count	36	31	67
	% within Genre	53.70%	46.30%	100.00%
	% within Country	0.20%	0.20%	0.20%
	% of Total	0.10%	0.10%	0.20%
Jazz	Count	558	251	809
	% within Genre	69.00%	31.00%	100.00%
	% within Country	3.00%	1.40%	2.20%
	% of Total	1.50%	0.70%	2.20%
Latin	Count	1453	34	1487
	% within Genre	97.70%	2.30%	100.00%
	% within Country	7.80%	0.20%	4.10%
	% of Total	4.00%	0.10%	4.10%
New Age	Count	4	24	28
	% within Genre	14.30%	85.70%	100.00%
	% within Country	0.00%	0.10%	0.10%
	% of Total	0.00%	0.10%	0.10%
Pop	Count	3773	7070	10843
	% within Genre	34.80%	65.20%	100.00%
	% within Country	20.20%	40.00%	29.80%
	% of Total	10.40%	19.50%	29.80%
Rap/Hip-hop	Count	553	507	1060
	% within Genre	52.20%	47.80%	100.00%
	% within Country	3.00%	2.90%	2.90%
	% of Total	1.50%	1.40%	2.90%
Reggae/Ska	Count	35	228	263
	% within Genre	13.30%	86.70%	100.00%
	% within Country	0.20%	1.30%	0.70%
	% of Total	0.10%	0.60%	0.70%
Rock	Count	3839	3255	7094
	% within Genre	54.10%	45.90%	100.00%
	% within Country	20.60%	18.40%	19.50%
	% of Total	10.60%	9.00%	19.50%
Seasonal	Count	127	188	315
	% within Genre	40.30%	59.70%	100.00%
	% within Country	0.70%	1.10%	0.90%
	% of Total	0.30%	0.50%	0.90%
Soul/R&B	Count	2713	945	3658
	% within Genre	74.20%	25.80%	100.00%
	% within Country	14.50%	5.30%	10.10%
	% of Total	7.50%	2.60%	10.10%
Soundtracks	Count	169	220	389
	% within Genre	43.40%	56.60%	100.00%
	% within Country	0.90%	1.20%	1.10%
	% of Total	0.50%	0.60%	1.10%
Vocals	Count	402	286	688
	% within Genre	58.40%	41.60%	100.00%

	% within Country	2.20%	1.60%	1.90%
	% of Total	1.10%	0.80%	1.90%
World	Count	113	85	198
	% within Genre	57.10%	42.90%	100.00%
	% within Country	0.60%	0.50%	0.50%
	% of Total	0.30%	0.20%	0.50%
Total	Count	18679	17666	36345
	% within Genre	51.40%	48.60%	100.00%
	% within Country	100.00%	100.00%	100.00%
	% of Total	51.40%	48.60%	100.00%