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Uncovering potential distinctive acoustic features of healing music

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ABSTRACTS

Background Music therapy is a promising complementary intervention for addressing various mental health conditions. Despite evidence of the beneficial effects of music, the acoustic features that make music effective in therapeutic contexts remain elusive.

Aims This study aimed to identify and validate distinctive acoustic features of healing music.

Methods We constructed a healing music dataset (HMD) based on nominations from related professionals and extracted 370 acoustic features. Healing-distinctive acoustic features were identified as those that were (1) independent from genre within the HMD, (2) significantly different from music pieces in a classical music dataset (CMD) and (3) similar to pieces in a five-element music dataset (FEMD). We validated the identified features by comparing jazz pieces in the HMD with a jazz music dataset (JMD). We also examined the emotional properties of the features in a Chinese affective music system (CAMS).

Results The HMD comprised 165 pieces. Among all the acoustic features, 74.59% shared commonalities across genres, and 26.22% significantly differed between the HMD classical pieces and the CMD. The equivalence test showed that the HMD and FEMD did not differ significantly in 9.46% of the features. The potential healing-distinctive acoustic features were identified as the standard deviation of the roughness, mean and period entropy of the third coefficient of the mel-frequency cepstral coefficients. In a three-dimensional space defined by these features, HMD's jazz pieces could be distinguished from those of the JMD. These three features could significantly predict both subjective valence and arousal ratings in the CAMS.

Conclusions The distinctive acoustic features of healing music that have been identified and validated in this study have implications for the development of artificial intelligence models for identifying therapeutic music, particularly in contexts where access to professional expertise may be limited. This study contributes to the growing body of research exploring the potential of digital technologies for healthcare interventions.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Music therapy is a promising intervention for various mental health issues, especially via the internet, but the selection of appropriate therapeutic music can be challenging, particularly in emergency situations.

WHAT THIS STUDY ADDS

⇒ This study identified several acoustic characteristics of healing music through comparative analyses with control music datasets. The identified healing-distinctive acoustic features were validated and their correlation with perceived emotional states was examined using independent music datasets.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ The findings of this study have implications for the development of music recommendation systems and artificial intelligence models capable of automatically identifying therapeutic music.

INTRODUCTION

Mental health issues such as depression, anxiety and stress have become increasingly prevalent.[1] Although many treatment options are available, including medication and psychotherapy,[2] music has emerged as a powerful tool for emotional relief.[3] Many people use music to cope with challenging emotions. Clinically proven music therapy has been found to be an effective intervention approach for a wide range of mental health issues.[4] Music therapy involves using music to address emotional, cognitive and social needs and has been shown to help reduce symptoms of depression, anxiety and post-traumatic stress disorder.

In clinics, music therapists use a range of techniques, including playing instruments, singing and listening to music, to address the physical and emotional needs of their clients.[5] Music therapy approaches can be divided into two main types based on how music is employed: active and receptive. Active music therapy involves patients actively participating in the music-making process, whereas receptive music therapy entails patients listening mainly to therapist-selected music pieces. These two approaches have widespread application in clinical practice.[6] Compared with the active method, the receptive approach is relatively more feasible and cost-effective, particularly given recent social distancing measures. Furthermore, the receptive method is flexible and suitable for patients of all ages with varying psychological and physical capabilities.[7] Regardless of the music therapy approach, music plays an essential role as the principal means for promoting emotional and cognitive expression, relaxation and connection. In receptive music therapy, carefully selecting appropriate music pieces is crucial for efficacy.

Most therapists choose pieces based on their expertise because extensive professional experience is required to determine whether a piece of music is helpful. According to the results of a comparison study on the anxiety reduction effect of therapeutic music (collected by professional therapists), Spotify playlist songs, songs chosen by several music recommendation algorithms, and therapeutic music yielded the most significant anxiety reduction.[8] The latter study demonstrates the significant therapeutic power of music, which is consistent with previous clinical knowledge[7] as well as a recent meta-analysis on the effects of music interventions on stress-related outcomes. The results of the meta-analysis showed that the effect size of the music selection by the music therapists was larger than that based on the patients' own preferences.[4]

Although professional selection is the gold standard, manual selection cannot meet the rapidly growing demand for therapeutic music in emergency situations such as infectious disease outbreaks. Revealing the specific characteristics of professionally selected therapeutic music will significantly contribute to the development of artificial intelligence models for automatically identifying therapeutic music. Some musical elements are believed to create a sense of calm and promote relaxation, making them more effective for therapeutic purposes, such as slower tempo, simple melodies and repetitive rhythms. Others have suggested that the healing effects of music are more about the emotional response that music elicits rather than any specific musical features.[9] However, music therapists do not simply play relaxing music for patients during interventions. Instead, music therapists use music to stimulate and release the treated person's emotional experience, which may include negative feelings such as depression, sadness, pain and anger.[10] Furthermore, some researchers argue that the idea of healing music is problematic because it implies that certain types of music are inherently more beneficial than others.[11] This can lead to the exclusion of musical genres and styles that may be meaningful and healing for certain individuals. While some argue that certain musical elements contribute more to the therapeutic effects of music than others, there is no clear consensus on whether or how acoustic features define healing music.

Therefore, this study aimed to investigate whether healing music has certain acoustic characteristics and universality and whether it is discernible compared with regular music by comparing the characteristics of healing music with other music in multiple dimensions.

METHODS

Participants and procedure

To our knowledge, no healing music dataset (HMD) is currently available for research purposes. To construct a dataset suitable for our study, an in-house questionnaire was developed according to our research needs and distributed via an online questionnaire platform (see online supplemental materials) in 2021. We received 42 completed questionnaires from participants throughout the country. Participants provided informed consent for inclusion in this study. The study was conducted in accordance with the Declaration of Helsinki. Our inclusion criteria were participants who had been engaged in music therapy or related research for at least 3 years and had achieved college level or higher education. The exclusion criteria were incomplete questionnaire data, obvious random responses, non-music therapy personnel and no relevant clinical work experience. Applying our inclusion and exclusion criteria, we excluded seven questionnaires (figure 1), including four with incomplete questionnaire data, one with random responses and two from non-music therapy personnel.

The participants in this study had an average of 10.03 (8.53) years of professional experience; 17.5% were males and 82.5% were females. The educational backgrounds of the participants included 5% college and below, 55% bachelor's degrees, 17.5% master's degrees and 22.5% doctoral degrees. The occupational backgrounds of the participants included 30% doctors, 22.5%

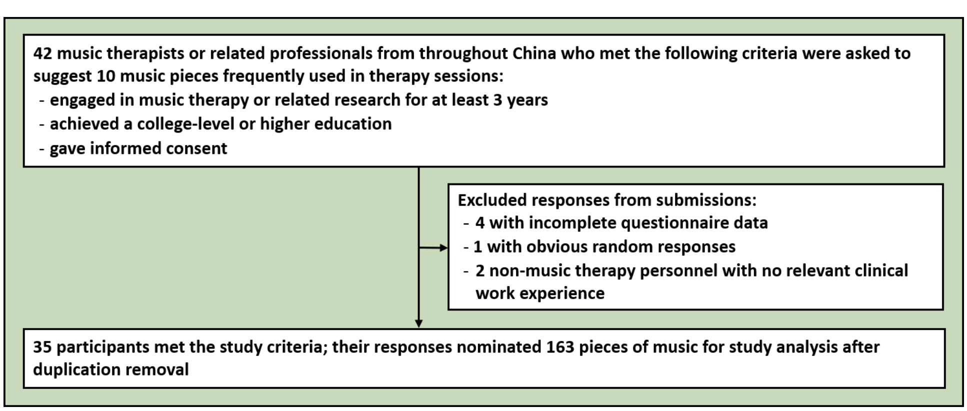

Figure 1 Flowchart for enrolment of participants and the number of music pieces analysed.

Ding Y, *et al. General Psychiatry* 2023;**36**:e101145. doi:10.1136/gpsych-2023-101145

music therapists, 37.5% psychotherapists and 10% rehabilitation therapists.

Participants were instructed to suggest no more than 10 pieces of pure music that they frequently used in daily therapy or believed to be helpful for emotional and other mental health issues. The raw data (see online supplemental materials) were subsequently compiled and proofread by two independent researchers. After removing redundancies in the nominations, music files with 165 pieces of music were gathered to form the basis of our HMD.

Control datasets

To identify and validate the potential healing-distinctive acoustic features, the following four control datasets were adopted in the present study.

Classical music: MusicNet dataset

The MusicNet dataset is a comprehensive compilation of classical music recordings consisting of 330 classical music pieces written by 10 composers and played on 11 instruments. The recordings were performed in various studio and microphone conditions for 34 hours. The duration of the pieces ranges from 55.25 s to 1069.04 s (mean (standard deviation, SD): 372.33 (195.71) s).[12]

Five-element music dataset (FEMD)

This study used a control dataset of five-element music derived from the 'traditional five-element music of Traditional Chinese Medicine (Normal Mode)'. This dataset was issued by the China Medical Audiovisual Publishing House and is commonly cited and acknowledged by relevant practitioners. This dataset comprises 225 min of music for the five elements, namely tonic, supertonic, mediant, subdominant and dominant, with each element having a duration of 45 min. To ensure comparability with the HMD, the dataset was divided into 50 segments, with each segment having a duration of 270 s.[13]

Jazz music: GTZAN dataset

The GTZAN dataset is the most frequently employed public dataset for assessing the efficacy of machine listening in music genre recognition research. The dataset files were amassed between 2000 and 2001 from diverse sources, including personal CDs, radio recordings and microphone recordings, to represent a range of recording conditions. It consists of 1000 distinct, 30 s audio excerpts of music, each singly labelled in one of 10 genres. The present research employed a set of 100 jazz music excerpts drawn from the dataset that have durations ranging from 30.01 to 30.48 s (mean (SD): 30.03 (0.08) s).[14]

Emotional music: Chinese affective music system

The Chinese affective music system is a standardised collection of musical stimuli designed for emotional research conducted by Chinese participants. The system comprises 300 distinct music clips, each lasting 30–60 s (mean (SD): 54.06 (12.42) s). The music selection covers seven distinct emotional states: happiness, calmness, sadness, fear, disgust, anger and surprise. Each music clip is accompanied by a set of indicator data, including measures of 'emotional intensity', 'recognition', 'valence', 'arousal', 'dominance', 'trend' and 'familiarity'. The present study used the 'valence' and 'arousal' ratings determined by the average scores provided by 200 individuals.[15]

Acoustic feature extraction

The mirfeature function of the MIRtoolbox (v1.7.2), a MATLAB toolbox, was used to perform a comprehensive comparison of the acoustic features between the HMD and control datasets. This function was executed with the option 'Stat', which generated 370 statistical parameters of acoustic features. These features were grouped into five dimensions: (1) the dynamic field, which is related to changes in energy over time and variations in volume and loudness; (2) the rhythm field, which pertains to the tempo and beat of the music; (3) the timbre field, which refers to the spectrum analysed by auditory models; (4) the pitch field, which relates to the fundamental frequency (f0) and harmonicity; and (5) the tonal field, which computes features related to energy and its time evolution when associated with musical keys. A detailed description of all acoustic features can be found in the MIRtoolbox manual.[16]

Statistics

Kruskal-Wallis test

In this study, Kruskal-Wallis (KW) tests were performed to examine the influence of genres on acoustic features, with the significance level set at p=0.05 after multiple comparison corrections. This non-parametric test was chosen because of the non-normal distribution of data and unequal sample sizes among the groups.

Wilcoxon rank-sum test

Wilcoxon rank-sum tests were used to compare the two datasets. This non-parametric test was selected because of its robustness against non-normality assumptions and ability to manage small sample sizes. Two-tailed p values were computed to determine whether the medians of the two groups were significantly different. The significance level was set at p=0.05 after multiple comparison corrections.

Equivalence test

The two one-sided test (TOST) approach was used to assess the equivalence between HMD and FEMD.[17] This approach involves TOST to determine whether the difference between groups falls within a prespecified equivalence margin or interval. This method allows for a formal assessment of the null hypothesis that the groups are equivalent or the alternative hypothesis that they are not. The upper and lower equivalence bounds were set to 0.5, as the effect size of interest, and the significance level for each one-sided test was set to ensure an overall significance level of 0.05 for the TOST procedure.

Multiple comparisons

To correct for the possibility of false-positive results owing to multiple comparisons, the false discovery rate (FDR) method was employed. FDR is a commonly used approach to adjust p values to control for the expected proportion of false-positive results among significant results. Specifically, the Benjamini-Hochberg procedure was used to calculate an adjusted p value for each hypothesis test based on the ranking of its original p value in the list of all tests and the overall number of tests conducted.

Machine learning

Classification

To distinguish classical pieces in the HMD from those in the classical music dataset (CMD), a random forest classification was performed. The model was constructed using 10 trees and evaluated using a holdout cross-validation approach with a split ratio of 0.3. Owing to the large imbalance in the number of samples, a binary classification process was conducted 5000 times, with each circle randomly selecting 40 samples from each category. In addition to holdout cross-validation, the performance of the model was assessed using a permutation test with 5000 iterations and evaluated based on accuracy and the area under the curve (AUC).

Regression

Linear regression was used to analyse the association between the three potential healing-distinctive acoustic features with subjective valence and arousal ratings. The precision of the linear regression model was evaluated using a leave-one-sample-out validation method, where the model was trained on all available data points except for one and subsequently tested on the excluded data point. This process was iterated for each data point, and the performance of the model was assessed by comparing the predicted and actual values. The significance of the regression coefficients was determined by their corresponding p values, and the overall goodness of fit of the model was evaluated using the r value. Moreover, the minimum square errors were compared with those of a permutation test with 5000 iterations using one-sample t tests.

Clustering

The k-means clustering algorithm was employed in this study for the unsupervised grouping of the subjective valence and arousal ratings based on the similarity in the potential healing-distinctive acoustic features, where k was set to 2. Each cluster was defined by its centroid, the mean feature vector of all the data points within the cluster. The algorithm iteratively minimised the sum of the squared distances between data points and their assigned centroids until convergence was reached.

All statistical and machine learning algorithms were executed using custom MATLAB scripts (v2021a; MathWorks, Natick, Massachusetts, USA).

RESULTS

An HMD was created through an in-house questionnaire completed by 35 qualified participants with at least 3 years of experience in music therapy or related research and college or higher education. A total of 165 pieces of music were selected by the participants. The duration length of each piece ranged from 71.27 s to 998.09 s (mean (SD): 261.09 (130.02) s). The pieces were derived from nine different genres: classical, electronic, rhythm and blues (R&B), soundtrack, folk, magic, march, New Age and pop. As shown in figure 2A, classical music accounted for the largest proportion (28.48%) of the genres, followed by pop music (17.58%). None of the remaining genres accounted for more than 15% of the total. Among all the pieces, 44 (26.67%) were nominated by more than one participant. The most recognised healing music is 'Castle in the Sky' by the Japanese musician Joe Hisaishi, which was nominated by five participants.

To comprehensively explore the potential distinctive acoustic features in healing music, 370 statistical parameters were extracted using the MIRtoolbox in MATLAB. KW tests were conducted to examine the influence of genre on these acoustic features, and the results showed that among all the acoustic features, 25.41% were significantly influenced by genre (FDR corrected $p<0.05$). In other words, the remaining acoustic features shared commonalities across genres.

To determine whether these commonalities contributed to the healing properties of the music, two control music datasets were considered: (1) a CMD for comparison with the classical pieces in the HMD and (2) a FEMD, which is another recognised HMD. The Wilcoxon rank-sum tests demonstrated that 26.22% of the acoustic features were significantly different between the healing pieces in the HMD (n=47) and CMD (n=330) groups at the FDR-adjusted alpha level of 0.05. Specifically, the ninth coefficient of the delta mel-frequency cepstral coefficients (MFCCs) was the most distinguishable acoustic feature in terms of the largest absolute z value ($z=4.77$, adjusted $p<0.001$), as shown in figure 2B. A random forest classification model was used to confirm these differences (figure 2C). The AUC was 68.93% (95% confidence interval (CI): 68.63% to 69.23%), and the accuracy (68.92%) was significantly higher than the empirical chance level (49.48%) derived from the permutation test (one-sample t-test, $t(4999)=-142.80$, $p<0.001$). Equivalence tests were conducted to identify the dimensions in which both HMDs were similar (see the Methods section). The results of the TOST showed strong evidence that HMD (n=165) and FEMD (n=50) did not differ significantly for 9.46% of the acoustic features. By combining these analyses, the standard criteria for acoustic features with healing properties were defined as:

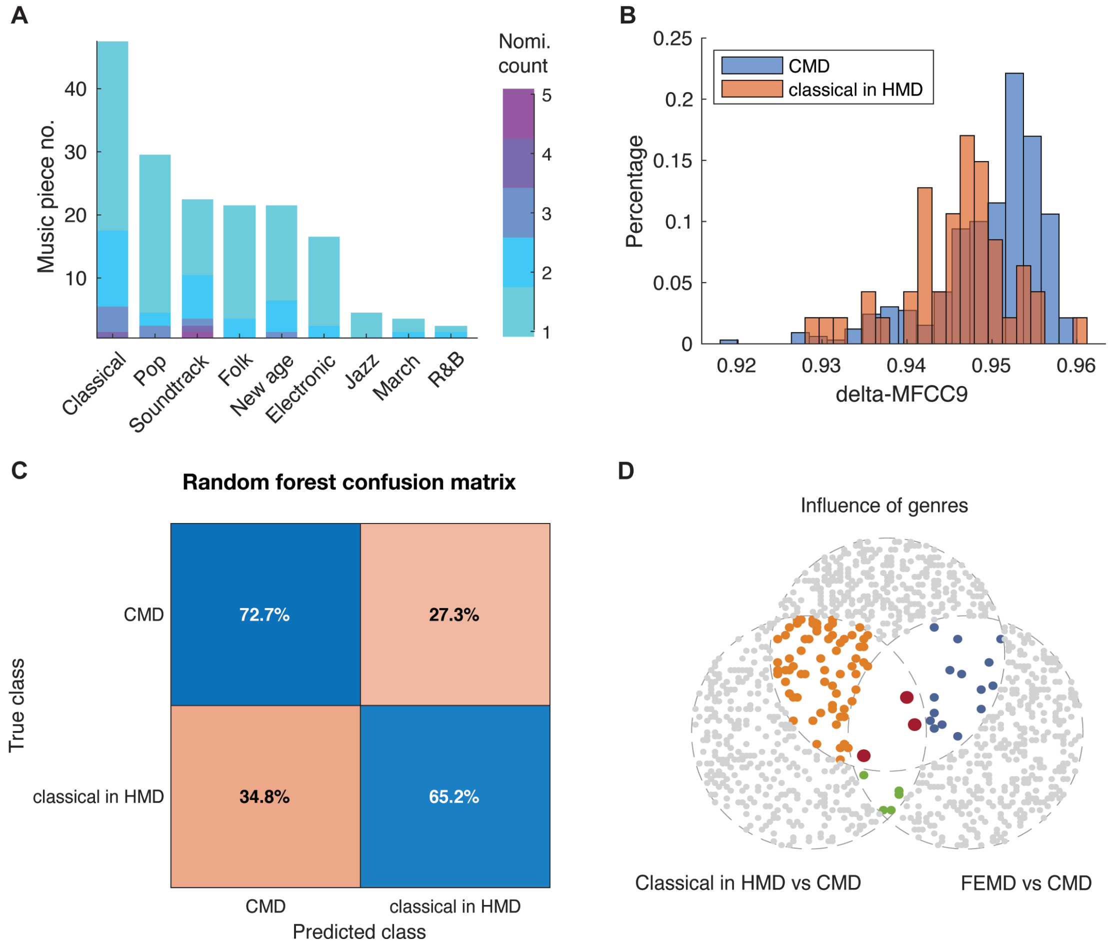

Figure 2 HMD and the comparison with other music datasets. (A) Music nomination frequencies across genres in HMD. (B) The distribution of the delta MFCC9 in the CMD (blue) and the classical pieces in HMD (red). (C) The confusion matrix of the random forest classifier separates CMD from the classical pieces in HMD. (D) The demonstration of the identification of the healing-distinctive acoustic features, where each dot indicates one feature. CMD, classical music dataset; FEMD, five-element music dataset; HMD, healing music dataset; MFCC, mel-frequency cepstral coefficient; no., number; Nomi., nomination; R&B, rhythmand blues.

(1) not influenced by the genre, (2) difference between healing pieces and regular pieces within the same genre, and (3) similarity across different HMDs. Based on this, the potential distinctive acoustic features of healing music were identified as the SD of the roughness, mean and period entropy of MFCC3 (figure 2D).

These three features were further confirmed by comparing the jazz pieces in an HMD with those in a jazz

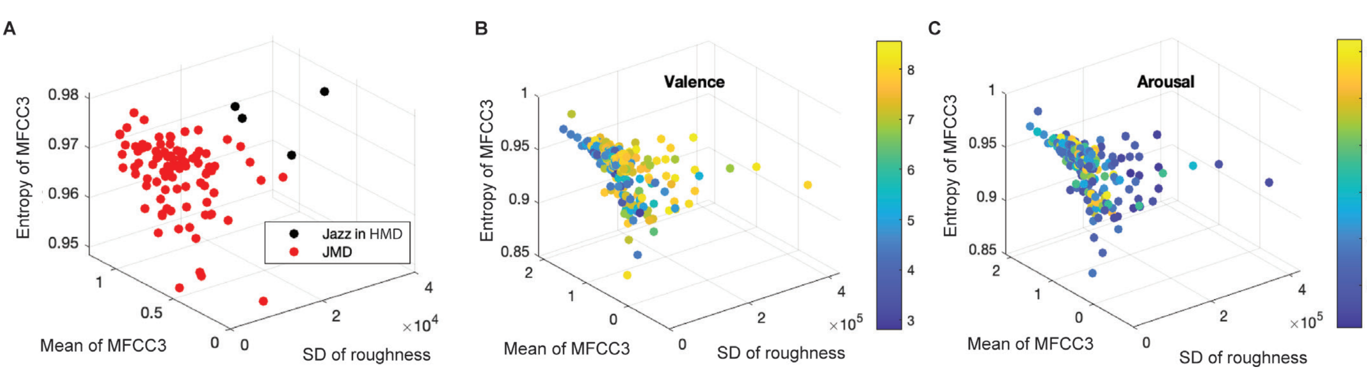

Figure 3 Validation of the healing-distinctive acoustic features and their relationship with perceived emotion. (A) The locations of JMD (red) and the jazz pieces in HMD (black) in the 3D space constructed with the three distinctive features. (B) The distribution of the subjective valence ratings (indicated by colour) in the 3D space constructed with the three distinctive features. (C) The distribution of the subjective arousal ratings (indicated by colour) in the 3D space constructed with the three distinctive features. HMD, healing music dataset; JMD, jazz music dataset; MFCC, mel-frequency cepstral coefficient; 3D, three-dimensional; SD, standard deviation.

music dataset (JMD). As shown in figure 3A, based on the three potential healing-distinctive acoustic features, the four jazz pieces in the HMD were clearly different from those in the JMD. Additionally, by adopting an emotional music dataset, the relationship between the three features and perceived emotion was examined using both supervised and unsupervised machine learning approaches. The healing-distinctive acoustic features significantly predicted both the subjective valence ($r=0.20$, $p<0.001$) and arousal ($r=0.27$, $p<0.001$) ratings, with a significantly smaller mean square error compared with the permutation tests (one-sample t-test, valence: $t(4999)=631.78$, $p<0.001$; arousal: $t(4999)=391.75$, $p<0.001$). When the emotional ratings were separately clustered into two clusters in the valence and arousal domains (figure 3B,C), the ratings in the two clusters were also significantly different (Wilcoxon rank-sum test, valence: $z=3.83$, $p<0.001$; arousal: $z=-4.41$, $p<0.001$).

DISCUSSION

Main findings

This study aimed to identify the distinctive acoustic features of healing music. Through a series of comparative analyses with several control music datasets, it was found that the SDs of roughness, mean and period entropy of MFCC3 exhibited the desired attributes as they were not impacted by genre, differed between healing pieces and regular pieces within the same genre, and were consistent across various HMDs. Furthermore, these three features and their correlations with perceived emotions were validated using independent music datasets.

Classical music is renowned for its refined and balanced melodies, as well as its harmonious rhythms. Although not specifically created for therapeutic purposes, classical music is believed to have a calming effect that promotes dopamine release[18] and suppresses cortisol production.[19] Unsurprisingly, classical music was the most frequently selected genre in this study (figure 2A). Classical music has long been associated with relaxation, stress reduction and emotional regulation. It has been shown to activate brain regions linked to positive emotions[20] while decreasing activity in regions connected to negative emotions.[21] It has also been used in therapeutic settings because of its potential to produce a calm state and promote healing. The present findings suggest that music therapists may be inclined to use classical music as a therapeutic intervention because of its broad recognition as a complex and sophisticated genre. Although classical music has been found to have therapeutic effects in numerous cases, not all classical music is guaranteed to have this effect.[22] As shown in figure 2C, the classical pieces in the HMD were considered distinct from the general CMD. Statistically, 26.22% of acoustic features were significant. Other musical genres may also have similar healing properties, as nine genres were identified as healing music.

This study hypothesised that healing music possesses shared acoustic features that transcend different genres and categories. This notion aligns with prior research indicating that music is a universal language that surpasses cultural and genre boundaries,[23] thus making it a potential therapeutic tool for individuals from diverse backgrounds. Apart from widely recognised music genres such as classical music, unique musical forms are passed down through history and tradition in certain cultures. These forms include pilgrimage songs in Nigeria, highlife drumming in Ghana, singing bowl music in India and five-element music in China.[24] The present study adopted five-element music as the recognised healing music, considering the cultural context of the participants. Traditional Chinese music is based on the five-element theory and the laws of Yin and Yang, which correspond to the elements of wood, fire, earth, metal and water. Using different melodies and rhythms, five-element music is thought to regulate the balance between the body and mind.[25] Although the therapeutic effects of these unique forms of traditional music have not yet been fully scientifically proven, they are used extensively and promoted. In addition to their shared recognition of healing effects, five-element music and regular therapeutic music differ significantly in several respects. The acoustic features identified through equivalence analysis in this study are likely to be relevant to healing effects. An equivalence test was conducted to assess the similarity between HMD and FEMD in terms of acoustic features. The lack of significant difference between the two datasets in a subset of acoustic features suggests that these features are shared or exhibit similar patterns for both types of music. This indicates that certain acoustic characteristics transcend specific music genres and are potentially representative of healing music in distinct categories. The identified acoustic features that showed equivalence between the HMD and FEMD can be considered potential markers or indicators of healing music. These features, which exhibited similar values or patterns in both datasets, likely contribute to the overall therapeutic or emotional impact of healing music. By highlighting these shared acoustic features, our study provides insight into the distinctive nature of healing music and contributes to our understanding of its underlying characteristics. It is important to note that although some acoustic features showed equivalence, others exhibited significant differences between the two datasets. This suggests that there are unique acoustic attributes specific to healing music. By identifying these distinct features, we can contribute to a more comprehensive understanding of the acoustic profile of healing music, which can inform the development of music recommendation systems and support the identification of therapeutic music. Along this line of research, incorporating a wider range of therapeutic music types into future studies may be worthwhile to validate further the identified potentially unique acoustic features related to therapeutic effects.

The results of this study show that certain acoustic features are more important than others in identifying healing music. Specifically, the SDs of the roughness, mean and period entropy of MFCC3 were identified as the potential distinctive acoustic features of healing music. Understanding the significance of these features can contribute to the development and evaluation of new music compositions. The SD of roughness pertains to the variation in the roughness of the audio signal, which is an indicator of the perceived irregularity or noise of the sound.[26] The roughness of music alludes to the subjective perception of the dissonance or noise of the sound. In the fields of music theory and psychoacoustics, roughness is recognised as the extent of beating or 'rough' sensation produced by the interaction between two or more sound waves that are in close frequency proximity but not in perfect alignment.[27] Given its ability to create different moods and emotional responses in listeners, roughness is an essential perceptual feature of music.[28] For example, dissonant intervals in music with a high roughness can evoke feelings of tension or suspense, whereas consonant intervals in music with smoother sounds can evoke a sense of relaxation or resolution. MFCCs are a concise set of features used to describe the overall shape of a spectral envelope in an audio signal associated with timbre.[29] MFCCs extract the spectral characteristics from signals and present them in a more condensed form. Each coefficient of the MFCC vector typically represents a different level of audio signal characteristics. The initial few coefficients of the MFCC vector, MFCC1 and MFCC2, capture the low-level characteristics of the signal, such as the energy and spectral slope. Conversely, higher order coefficients, such as MFCC4 and above, capture the fine-grained characteristics of the signal, such as the inter-relationships between resonance peaks. Therefore, MFCC3, which is the third MFCC coefficient, plays a crucial role in capturing the intermediate-level features in the signal. The potential utility of MFCC3 lies in its ability to provide information about various sound characteristics such as timbre and pitch, making it useful for audio recognition and music processing.[30] Speech studies have found that MFCC3 is related to depression.[31] However, the role of MFCC3 and its statistics in music require further exploration.

Limitations

Although we aimed to uncover universal healing features, cultural factors may have influenced the generalisability of our findings. Hence, it is essential to consider cultural diversity when applying these features to guide the future selection and generation of healing music and to conduct corresponding analyses and adjustments. Additionally, owing to the limited number of participants, the sample size of our questionnaire-based population was relatively small. Thus, collecting and analysing a larger scale HMD in the future may contribute to obtaining more representative results. Although we endeavoured to explore the relationship between the three identified features and perceived emotions by comparing them with an emotional music library, a gap remains between healing effects and perceived emotions. Future studies should devise methods to quantitatively measure the impact of these three parameters on healing effects with precision adjustments. Exploring the impact of these parameters on other physiological and psychological indicators may provide a more comprehensive understanding of the potentially distinctive acoustic features of healing music. Finally, incorporating qualitative analysis methods could enrich the interpretation of the results by elucidating the participants' subjective experiences and meanings of music.

Implications

In summary, this study successfully identified the potentially unique acoustic characteristics of healing music, which could be advantageous for devising novel music therapies or assessing the efficacy of existing therapies. These identified acoustic features can serve as key indicators of music that elicit a calming and soothing response. By integrating these features into a music recommendation system, healthcare professionals can tailor personalised playlists for patients. Music recommendation systems that leverage artificial intelligence algorithms can analyse a patient's physiological and psychological responses in real time through relevant biometric measures. This allows for continuously monitoring and adjusting music playlists to optimise therapeutic outcomes. Furthermore, the system can learn from the patient's feedback and adapt recommendations over time, ensuring a more personalised and effective intervention. These technologies can potentially reach larger populations, including those with limited access to professional expertise, and provide cost-effective and easily accessible music therapy interventions. Moreover, these outcomes offer evidence for the use of music as a universal therapeutic modality to overcome cultural and genre barriers. The implications of these findings can be applied in diverse contexts, such as music therapy for stress reduction, mental health and chronic pain management. Future research could confirm the generalisability of these findings by employing larger and more diverse samples of participants and expanding the types of healing music tested. Additionally, further research should investigate the underlying neural mechanisms linking these acoustic features to therapeutic effects.

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Competing interests None declared.

Patient consent for publication Not applicable.

Ethics approval This study involves human participants and was approved by the Shanghai Mental Health Center Institutional Review Board (ethics approval ID:

2021-45). Participants gave informed consent to participate in the study before taking part.

Provenance and peer review Not commissioned; externally peer reviewed.

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