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Predicting the Preference for Sad Music: The Role of Gender, Personality, and Audio Features

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ABSTRACT The ''tragedy paradox'' of music, avoiding experiencing negative emotions but enjoying the sadness portrayed in music, has attracted a great deal of academic attention in recent decades. Combining experimental psychology research methods and machine learning techniques, this study (a) investigated the effects of gender and Big Five personality factors on the preference for sad music in the Chinese social environment and (b) constructed sad music preference prediction models using audio features and individual features as inputs. Statistical analysis found that males have a greater preference for sad music than females do, and that gender and the extraversion factor are involved in significant two-way interactions. The best-performing random forest regression shows a low predictive effect on the preference for sad music ($R^2 = 0.138$), providing references for music recommendation systems. Finally, the importance-based model interpretation feature reveals that, in addition to the same music inputs (audio features), the perceived relaxation and happiness of music play an important role in the prediction of sad music preferences.

INDEX TERMS Sad music, music preference, individual difference, music recommendation, audio signal processing, music emotion perception.

I. INTRODUCTION

Due to the ability to convey and arouse emotions, music has occupied an important place in human life since ancient times. Although human beings avoid experiencing negative emotions, some people may enjoy the sadness portrayed through music [52]. The ''tragedy paradox'', usually appearing in an aesthetic context, has attracted a great deal of academic attention from both musicologists and psychologists. Previous studies have revealed that music preference is influenced by the musical environment, cultural environment, and individual characteristics [3]. Similarly, the preference for sad music may also depend on music features and individual factors.

Humans' preference for music (also for sad music) has similarities associated with music information input, such as audio features, generic styles, and referential meaning [3]. This is also the reason why popular music has successfully been repeatedly recommended in music recommendation systems [53]. On the other hand, humans' preference for sad music has characteristics related to individual emotional states, individual traits, and social context [59]. For instance, Garrido and Schubert revealed that liking sad music is correlated with absorption, rumination, fantasy, and empathic concern [69]. Although several individual factors have been examined in previous studies [69], [70], more individual variables need to be investigated in different environments. Thus, from a theoretical perspective, this study investigates the effects of individual factors (e.g., gender and personality) on the preference for sad music in the Chinese

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social environment (studying Chinese music and investigating Chinese listeners). In addition, from a practical perspective, the present work constructs prediction models of the preference for sad music by combining the similarity (music features) and individuality (individual factors) of music preference. We believe the constructed models can provide references for alleviating the cold start problem in music recommendation systems.

II. LITERATURE REVIEW

A. MUSIC PREFERENCE

Music preference is defined as the ‘‘listeners' liking for specific pieces of music compared with others at particular points in time'' [7], [14]. Both similarities and differences in music preferences have been observed between different individuals. The theoretical model of LeBlanc revealed that music preference depends on the input information (‘‘musical environment'' and ‘‘cultural environment'') and the listener's characteristics (e.g., gender, age, and musical ability) [3]. This section separately introduces the input information and individual characteristics influencing music preference. Music preference-based music recommendation systems and the cold start problem are then briefly mentioned.

1) MUSIC FEATURES INFLUENCING MUSIC PREFERENCE

Humans may have similar preferences for musical stimuli with similar musical structures. LeBlanc's interactive theory believed that the physical properties, complexity, and referential meaning of music, as well as the quality of the performance, are the direct music inputs that influence the music preference decision [3]. Various music features have been examined in previous psychological studies. For example, the work of [17] showed that generic styles, defined by the physical properties, influenced children's music preferences; LeBlanc's series of studies examined the effects of tempo and performing medium on music preferences [27]–[31], and different results were found in different age groups; Wapnick studied the pitch, tempo, and timbre preferences of music students, and found the consistent preference for fast tempo and bright timbre but no particular preference for pitch levels [18]; and the work of [21] observed that the strength of music preference covaried with the intensity of music use.

Since most of the previous studies are independent, Rentfrow, Goldberg, and Levitin summed up a novel five-factor model for interpreting the underlying structure of musical preferences [6]. The model, named MUSIC, contains Mellow (comprising smooth and relaxing styles), Urban (defined largely by rhythmic and percussive music), Sophisticated (including classical, operatic, world, and jazz music), Intense (defined by loud, forceful, and energetic music), and Campestral (comprising different styles of direct and rootsy music) factors. This model presented stability across different groups and transcended the genre features of music [19].

In sum, previous studies have confirmed the close relationship between music features and music preferences. The present study aims to examine the effect of the above mapping on the prediction of sad music preferences.

2) INDIVIDUAL FACTORS INFLUENCING MUSIC PREFERENCE

Individual differences in music preference have been widely studied in psychological research over the last two centuries [3], taking many factors into account [7]. Demographic factors, such as age, gender, and race, may be the most widely discussed features. A series of studies have suggested that listeners' age affects their music preferences [27]–[31]. Various studies have revealed that listeners' engagement with music changes across the lifespan [7]. Gender, as a primary social distinction, also influences music preferences. For example, Christenson and Peterson found that men had stronger preferences for southern rock, psychedelic rock, and blues than women [25]; Hargreaves, Comber, and Colley's work showed that British secondary schoolboys liked heavy metal and rock more than girls did [32]; and the results of [33] confirmed a greater preference of heavier contemporary music among men and of chart pop music among women. Nationality and race factors are usually examined in cross-cultural studies. For instance, the work of [38] examined the effects of black and white listeners' and performers' race on music preferences, and Teo, Hargreaves, and Lee investigated whether there were significant differences in preferences for Chinese, Malay, and Indian music by adolescent students from Singapore and the United Kingdom [40]. Most research has explored demographic factors separately, but some research has considered them together. For example, the work of [34] examined the effects of age, gender, and nationality on music listening preferences, finding that all factors were significant influences on music preference and that every variable was significantly involved in interactions.

Psychological factors were the other most researched and discussed type of factor. Personality factors may be one of the hottest psychological traits in music preference studies [43]–[46]. Previous research found that personality has a predictive influence on individuals' music preferences [39], [41]. Music preference is also a badge of identity, which human beings use as an indicator of their personality [36]. Other psychological factors were also separately considered in different studies. For example, the works of [48]–[49] found that individuals highly engaged with music showed greater a strength of preference for the music they like, and the recent work of Bonneville-Roussy *et al.* developed an integrated model containing various ‘‘psychological internal dispositions'', which include conformity, self-monitoring, and uniqueness seeking [42]. These studies gradually pieced together a mapping of the relationship between music preferences and psychological characteristics.

According to LeBlanc's interactive theory [3], some individual factors have been examined in previous works, whereas more factors still need to be studied in the future. Thus, the present study tested the effect of individual factors (e.g., gender and personality) on sad music preference. In addition, the application of theoretical results in real-world scenarios (e.g., music recommendation systems) was also considered.

3) MUSIC RECOMMENDATION AND THE COLD START PROBLEM

Music recommendation is the most common application for music preference prediction systems. From collaborative filtering methods in the early days to deep learning methods in recent studies [4], [24], [35], music recommendation systems have made considerable progress in the past two decades. However, the cold start problem still occurs in collaborative filtering-based recommendation systems [37]. The cold start problem in music recommendation systems is defined as the difficulty of generating recommendations for new items (new music or new users), because new items do not have feedback information [50], [101]. Thus, content-based methods and hybrid methods were proposed to address the cold start problem [47]. For example, Soleymani *et al.* developed a content-based method that estimated psychologically validated music attributes (MUSIC model [6]) from audio using sparse representation and auditory modulation features [37], and this method achieved significantly better performance than genre-based and user-based recommendations in the cold start scenario.

The above-proposed method is a direct use of individuals' similarity in music preferences. This raises the question of whether the similarity for music feature preferences and accessible individual information (individual factors introduced previously) can be used to alleviate the cold start problem (with a new user but not with a new item). In fact, the similarity in music preferences has been widely used in music recommendation systems. What we are most familiar with is following the distribution of popularity, which means recommending the most popular music [53]. Individual factors have been considered in video [54], recipe [51], friend [55], [56], and image [57] recommendation systems. Therefore, for sad music, this study would like to investigate the prequestion, that is, whether music features and individual factors can be used to predict sad music preferences.

B. PREFERENCE FOR SAD MUSIC

1) SADNESS IN EMOTION MODELS

Discrete emotion models that divide emotions into discrete categories and multi-dimensional emotion space models that use multiple dimensions to label emotions are two types of emotion models acknowledged by psychologists [80]. For discrete emotion models, Izard advocated to find limited basic emotions to define emotions, while other emotional experiences are a mixture of multiple basic emotions [81]. Therefore, based on different methods of defining basic emotions, different discrete emotion models were proposed, such as the six basic emotions (sadness, fear, happiness, anger, surprise, and disgust) proposed by Ekman [67], the wheel model proposed by Plutchik [82], and the ten basic emotions proposed by Izard [83], [84]. Among them, all discrete emotion models defined sadness as the basic emotion, showing the importance of sadness in the emotion models.

For multi-dimensional emotion space models, the valence-arousal (VA) model proposed by Russell [85] was one of the most classic emotion model, which has been widely used in not only psychological studies but also other fields, such as music emotion recognition (MER) [1] and human emotion recognition [80]. In fact, the discrete emotions are correlated with the dimensions in the VA models. For example, excitement has positive valence and high arousal while sadness has negative valence and low arousal. In addition, to better distinguish discrete emotions in multi-dimensional emotion space models, the VA model was extended by adding new dimensions, such as dominance [86] and depth [87].

Since sadness occupies an important position in different emotion models, it has been individually extracted and investigated in various studies, including the financial costs of sadness [88], effects of sadness on social perception [89], sad music preference [61], brain activity during sadness [90], and so forth.

2) TRAGEDY PARADOX IN MUSIC

Although sadness is one of the basic emotions that people seek to minimize, individuals often enjoy the sadness that is portrayed in music [52], [58]. The phenomenon of "pleasure sadness" has puzzled musicologists and psychologists for decades [61]. Sachs, Damasio, and Habibi found, after conducting a review, that the phenomenon (also called the "tragedy paradox") usually occurs in an aesthetic context [59]. The attraction of sad art may be associated with psychological rewards. Thus, psychologists have made great efforts to interpret the underlying mechanism. The work of [68] noted that music-perceived sadness may directly produce a positive feeling instead of feelings of sadness. However, other works argued that sad music can be felt as a mixed emotion containing both positive and negative aspects [65] or that sad music arouses special feelings of sadness, which then produce a positive affective state [52]. A series of neuroscience studies have also been conducted to investigate how the brain works and responds to music listening [63], emotion processing [61], [66], and aesthetic judgment [62], [64]. These studies have allowed us to gradually understand the causes of the preference for sad music.

Although the "tragedy paradox" frequently appears in everyday life, not everyone experiences a pleasurable response all the time to sad music. Individual differences in sad music preferences have been observed in several psychological studies. The work of [69] found that liking sad music is correlated with absorption, rumination, fantasy, and empathic concern. The openness and extraversion factors in the Big Five personality model are also associated with the preference for sad music [52], [70]. Mood is an important factor in determining whether sad music is enjoyed. Hunter, Schellenberg, and Griffith observed that individuals' liking of sad-sounding music increased after inducing sad moods in participants [71]. Taruffi and Koelsch found that some individuals would select sad music when they were sad, but others preferred to listen to happy music [72]. These studies presented individuality in the liking of sad music, which reminds us to consider individual factors in sad music recommendation systems.

Therefore, why should this study focus on predicting sad music preferences? As mentioned before, individual factors affect the liking of sad music, whereas the preference for sad music may also reflect an individual's traits and states. For example, one of the symptoms of major depressive disorder (MDD) is persistent sadness [73]. Compared with happy and neutral music, individuals with MDD were more likely to listen to sad music [74]. Thus, in addition to providing references for the music recommendation systems, predicting an individual's preference for sad music can also provide help in identifying individual traits or making inferences about mental illness.

C. FROM MUSIC EMOTION RECOGNITION TO MUSIC PREFERENCE PREDICTION

MER, a field investigating computational models for automatically recognizing the perceptual emotion of music, has made great progress in recent decades [91]–[94]. Kim *et al.* noted that MER usually constitutes a process of extracting music features from original music, forming the relations between music features and perceived emotions, and predicting the emotion of untagged music [95]. Since different people listening to the same music may produce different emotion perceptions [96], most MER studies predicted the average emotional assessment from a large number of emotion annotators. The work of Yang *et al.* [1] concluded after conducting a review that "MER is affected by strong subjectivity, because it involves emotions and has strong correlations with the human character, preference, and other factors." Therefore, Yang *et al.* have advocated to consider the individualities in MER studies [11]. Following Yang's work, many MER studies have investigated individual differences, including testing the effects of individual factors [13] and constructing personalized MER models [97], [98].

Similar to MER studies, music preferences also have commonalities and individualities. As mentioned before, music preference depends on the music information (same as the music features in MER studies) and the listener's characteristics [3]. To predict music preference, we should consider both music features and individual factors. Therefore, can we apply the methods in MER studies to music preference prediction? This is what the present work hopes to investigate.

D. THE AIM OF THIS STUDY

There are two aims of our study. First, from a theoretical perspective, we would like to investigate the effects of individual factors (e.g., gender and personality) on the preference for sad music. After controlling for some individual variables (e.g., age and music ability), the primary and interactive effects of the considered individual factors were then examined. We believe that theoretical discoveries based on psychological methods are an important basis for subsequent model construction. From a practical perspective, we constructed prediction models of sad music preference by using music features and individual features as inputs. The constructed models can provide references for solving the cold start problem in music recommendation systems.

III. METHODS

As shown in Figure 1, the present study contains three main components. First, in the behavioral experiment, music listening tasks were conducted to collect different individuals' preferences for sad music (ground truth data) and perceived emotions. Individual factors were also measured through questionnaires (see Section A). Section B then introduces the audio signal processing methods in this study. Finally, the construction of the models is introduced in Section C.

A. BEHAVIORAL EXPERIMENT

1) MUSICAL STIMULI

Sixty songs popular in China were first selected based on their perceived sadness. All songs are Chinese pop songs of the recent two decades, sung by different popular singers. Since the emotional content of a song fluctuates, the length of the segment for popular music is usually 25–30 seconds, corresponding to the typical length of the chorus part [8]. To ensure the stability of perceived emotions, the collected music excerpts were trimmed to 25 seconds in this study. Following the approach of [11], [13], the excerpts were then converted to a uniform format: 22,050 Hz, 16 bits, and mono channel PCM WAV. To objectively evaluate the degree of sadness of the songs, the perceived sadness rating of each excerpt was evaluated on a scale from 1 (not at all) to 5 (very much). Each excerpt was annotated 20 times by volunteers recruited from the campus. The mean perceived sad values of sixty excerpts are shown in Figure 2, and the excerpts with a value higher than 2 were regarded as sad music in this study. Both sad songs ($N = 35$) and nonsad songs ($N = 25$) were used as stimuli in the formal experiment, preventing participants from guessing the experiment's intention.

2) PARTICIPANTS

In this study, 95 participants recruited from the campus participated in our formal experiment. To control the participant's musical experience, the data of two participants who had received professional music training were excluded. Since all the participants were college students, the final 93 participants (40 males and 53 females) were aged 22.43 ± 2.20 years.

3) PROCEDURE

Referring to the procedure of previous psychological studies [12], [13], the present experiment was designed as follows. After a brief description of the experiment, participants received a listening order containing 12 music excerpts that

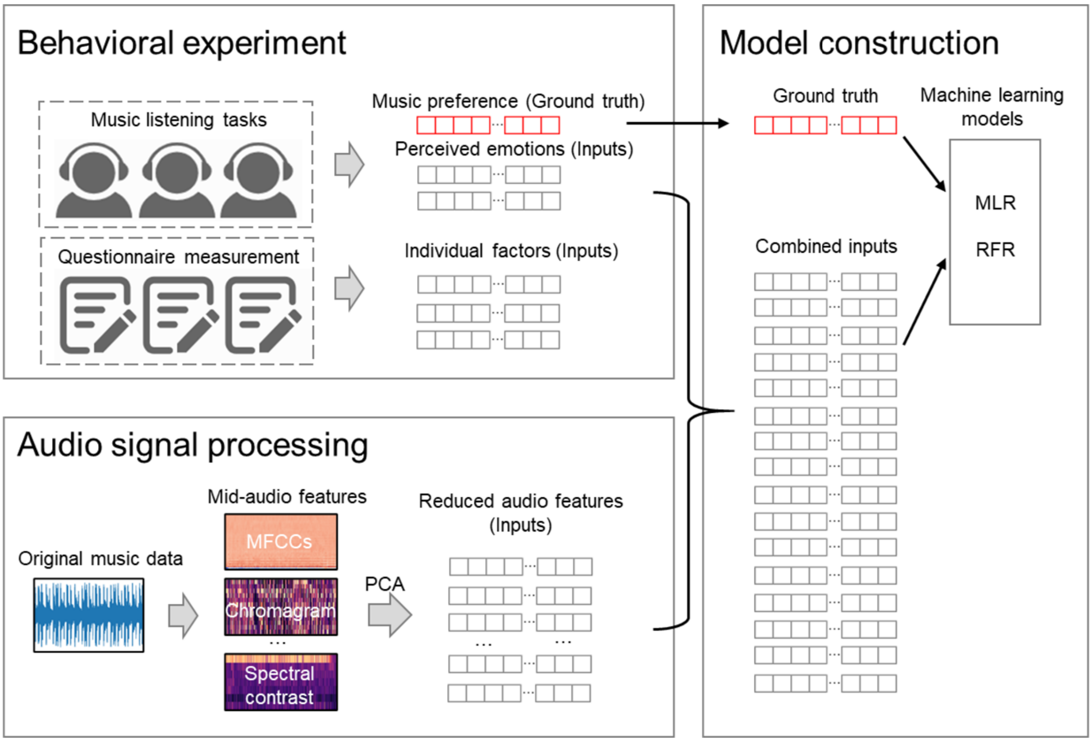

FIGURE 1. The framework of this study.

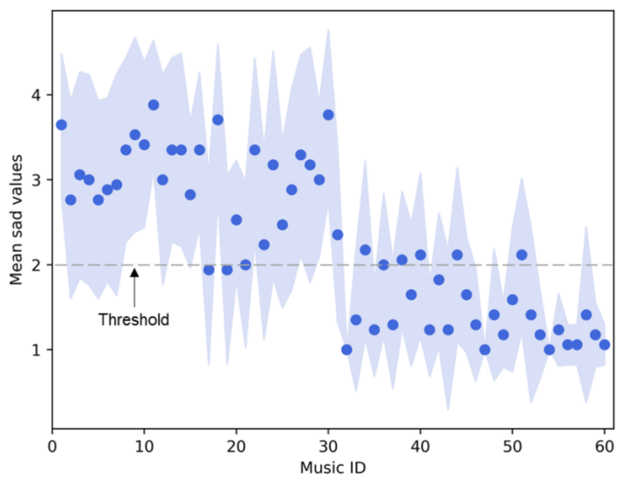

FIGURE 2. Mean perceived sad values of each music excerpt in this study. Error bars indicate the standard deviation.

were randomly selected from our stimuli sets. The listening order of each participant was independently randomized to minimize the influence of the presentation order [13]. As shown in Figure 3, each excerpt was preceded by 30 seconds of silence and followed by self-report questions. Referring to the scales in previous studies [13], [99], [100], the preference for the music was first evaluated on a scale of 1 (not at all) to 5 (very much). Then, the perceived sad emotion of the excerpt was evaluated (i.e., ''Do you perceive a sad emotion from this music?''). To prevent participants from guessing the experiment's intention, other perceived emotions (happy, angry, and relaxed) were also evaluated on scales from 1 (not at all) to 5 (very much). Similarly, the evaluation of the perceived emotions was randomly conducted to minimize the influence of the order of the songs. The above experiment processes were conducted by a program created by E-Prime 2.0. In addition, experiments were conducted in a quiet laboratory environment, and participants were asked to concentrate on the music and listen to the music with their eyes closed. The participants listened to the music by wearing headphones of same model.

After the music listening task, we first collected the age, sex, and music experience (e.g., whether they had received professional music training) information of each participant. Then, we measured the Big Five personality traits of each participant by using a Chinese-language 44-item Big Five Inventory personality scale [2].

In sum, in the behavioral experiment, we obtained 629 effective annotations of preferences for sad music (the annotations of nonsad music were removed for modeling) as well as perceived emotions. The gender and personality information of each individual were also collected. In addition, several individual factors (age and music education) were controlled to ensure the effectiveness of subsequent statistical analysis and modeling (data can be available at: https://github.com/xl2218066/PredictSadMusic).

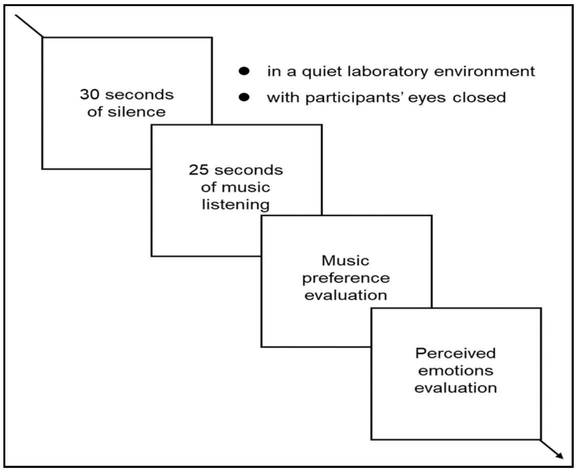

FIGURE 3. Experimental design of the music listening task.

B. FEATURE PROCESSING

1) AUDIO FEATURE PROCESSING

The traditional handcrafted feature-based methods, analyzing the low- and mid-level audio features [1], [9], were used for audio feature extraction. The present study considered spectral features, which reflect the intensity, timbre, and pitch of music, such as the mel-frequency cepstrum coefficients (MFCCs), spectral centroid, and chromagram [8], [22]. The rhythmic features (by beat and tempo detection) were also extracted.

To extract the spectral features, each excerpt was first sampled with a 22050 Hz sampling rate. Then, we used a short-term Fourier transform to obtain the power spectrogram. Computing the discrete Fourier transforms over Hann windows [15], we obtained a 1025×1077 spectrogram of each excerpt. After the above preprocessing, different spectral features were calculated. For example, for MFCCs, we used a Mel filter bank to filter the spectrogram, which generated a Mel-scaled spectrogram. Then, we selected the lower cepstral coefficients to compute the MFCCs [26]. The chromagram was computed using Ellis's approach [23], and the tonal centroid features were then calculated by projecting chromagram features onto a 6-dimensional basis. Other features, including spectral centroid, spectral contrast, spectral rolloff, and zero-crossing rate, were also computed through the librosa toolkit [10]. The spectral features and rhythmic features were then connected and reduced using principal component analysis (with 99% of the variance). The reduced features were finally used as audio inputs in subsequent modeling.

2) INDIVIDUAL FEATURES

The individual factors and the preference values were also processed for modeling. First, the continuous inputs (the Big Five personality values and the perceived emotion values) were scaled to a value between 0 and 1. Second, the gender feature, as binary input, was labeled as 0 (male) or 1 (female). Finally, the ground truth value (the preference for sad music) was also scaled to a value between 0 and 1. Notably, the above processing was only conducted for the modeling but not for the statistical analysis.

C. MODELING METHODS

The present study formulated sad music preference recognition as a regression problem. We used multiple linear regression (MLR) as the baseline algorithm and random forest regression (RFR) as the main algorithm. Because RFR has shown good performance in audio signal-related modeling tasks [13], we can easily interpret the constructed models by calculating feature importance [5].

To compare the effects of different inputs, three types of input sets were used: (a) audio features only; (b) individual features only; and (c) combining audio and individual features. Using audio features only can examine the commonality of human sad music preferences. Using individual features only can test the effects of the considered individual factors. The combination of audio and individual features was used to pursue the best prediction effect, and the feature importance was compared in this final model.

For each RFR, a grid parameter search was applied to find the best parameters (see Table 1). The performances of our models were evaluated by the ten-fold cross-validation technique, using 90% data as training data to train models and the remaining instances as testing data. And the above procedure is repeated ten times. The prediction accuracy of a regressor was measured using R^2 statistics.

TABLE 1. The best parameters for each random forest regression.

Parameters	Inputs		
	AF	IF	CF
n_estimators	17	39	99
max_depth	38	37	18
min_samples_leaf	28	47	23
min_samples_split	42	17	5
max_features	0.6	0.5	0.6

AF indicate audio features; IF indicate individual features; and CF indicate combined features.

IV. RESULTS

A. STATISTICAL ANALYSIS

As the first step of the exploration, we examined the relationship between the perceived sad ratings and the music preference values. As shown in Figure 4a, the perceived sad ratings are negatively correlated with the music preference values ($r(1115) = -0.122, p < 0.001$). This result reveals that, in general, people do not like sad music. The "tragedy paradox" only appears in some people or in some situations. We then tested the main effects of individual factors respectively. As shown in Figure 4b, each Big Five personality factor has no significant effect on the sad music preference, but males prefer to listen to sad music than females

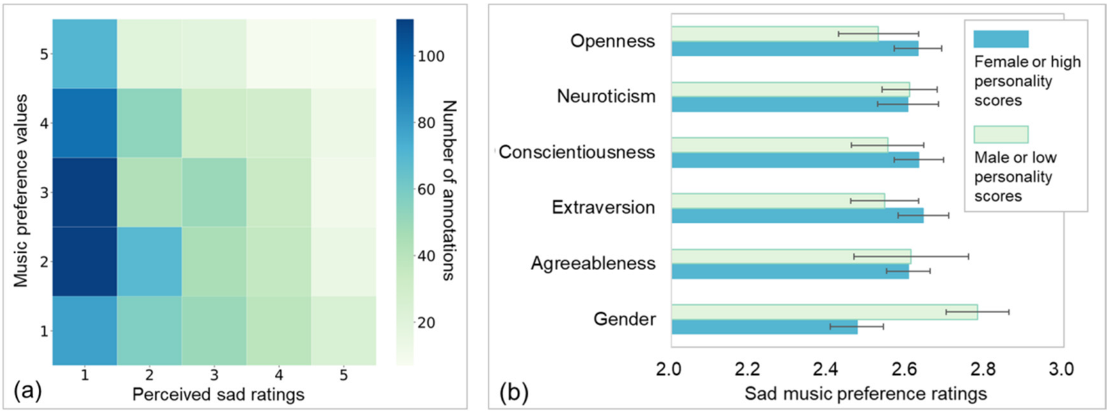

FIGURE 4. Correlation results and the main effects of individual factors. (a) Correlation between music preference values and perceived sad ratings. (b) The main effects of considered individual factors. Error bars indicate the standard errors.

TABLE 2. The interaction effects between gender and each personality factor on sad music preference.

Parameters	Type III Sum of Squares	Mean Square	F	Sig.
Intercept	1178.068	1178.068	702.901	0.000
Gender	0.018	0.018	0.011	0.917
Agreeableness	0.573	0.573	0.342	0.559
Gender * Agreeableness	5.779	5.779	3.448	0.064
Intercept	2890.466	2890.466	1725.769	0.000
Gender	4.448	4.448	2.656	0.104
Extraversion	0.770	0.770	0.460	0.498
Gender * Extraversion	**7.106**	**7.106**	**4.242**	**0.040**
Intercept	2991.934	2991.934	1780.011	0.000
Gender	**16.951**	**16.951**	**10.085**	**0.002**
Conscientiousness	0.783	0.783	0.466	0.495
Gender * Conscientiousness	3.379	3.379	2.010	0.157
Intercept	3727.668	3727.668	2215.481	0.000
Gender	**16.815**	**16.815**	**9.994**	**0.002**
Neuroticism	2.015	2.015	1.198	0.274
Gender * Neuroticism	0.750	0.750	0.446	0.505
Intercept	2980.741	2980.741	1773.378	0.000
Gender	**15.458**	**15.458**	**9.197**	**0.003**
Openness	2.324	2.324	1.382	0.240
Gender * Openness	1.104	1.104	0.657	0.418

(t = 2.936, p = 0.003). The interaction effects between gender and each personality factor were also examined using two-way ANOVA, and only the interaction between gender and the extraversion factor was significantly observed (see Table 2).

B. PREDICTION RESULTS AND MODEL INTERPRETABILITY

As mentioned before, we respectively used audio features, individual features, and the combined features as inputs to predict sad music preference. The performance of MLP and RFR algorithms was also compared. The constructed models were evaluated by the ten-fold cross-validation technique, and the prediction accuracy of each regressor was measured using the R^2 statistics. As shown in Table 3, the regressor using combined features and RFR performs best in predicting sad music preference values. For algorithms, ten-fold paired T test shows that, when using combined features, the RFR-based model does not perform significantly better than MLR-based model (t = 0.258, p = 0.802). For inputs, when using RFR algorithm, combined features-based model performs significantly better than individual features-based

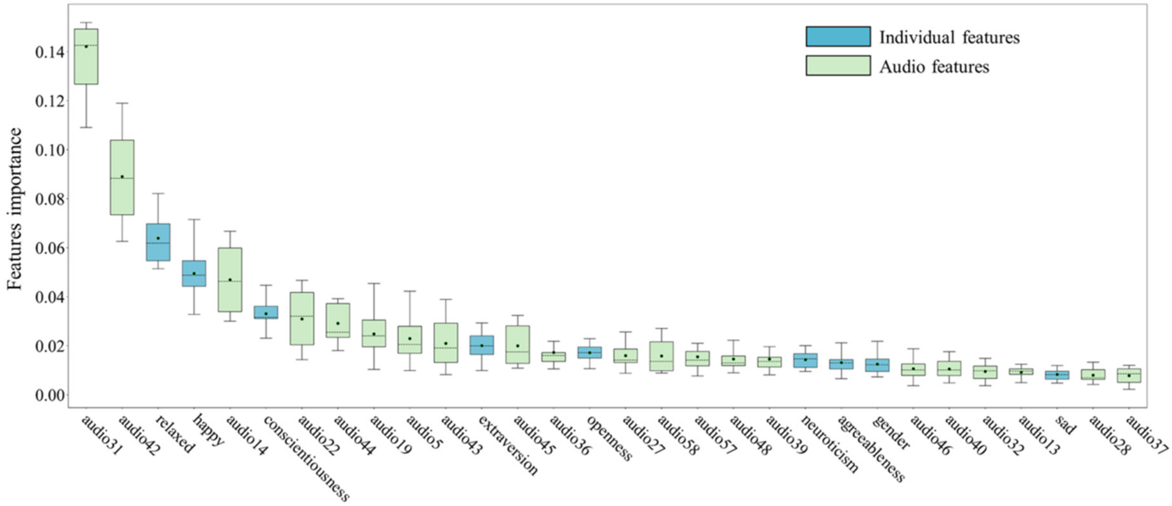

FIGURE 5. Distribution of importance of each feature for the best performing model. Boxplots are arranged in descending order of the mean value. The top 30 features are included for visibility, and the trend of the remaining features is approximately the same. The black dots indicate the mean values, and the black dotted lines indicate the median values. Audio31, audio42, audio 14, and audio 22 indicate the 31st,42nd, 14th, and 22nd PCA components, spectral centroid and spectral rolloff have the highest loadings in these components.

TABLE 3. The prediction accuracy of different regressors.

Inputs	Algorithms	R^2 (M±SD)
AF	MLR	-0.194 ± 0.775
	RFR	0.103 ± 0.095
IF	MLR	0.031 ± 0.084
	RFR	0.031 ± 0.070
CF	MLR	0.131 ± 0.089
	RFR	0.138 ± 0.109

AF indicate audio features; IF indicate individual features; and CF indicate combined features. MLR indicate the multiple linear regression; and RFR indicate the random forest regression.

model (t = 3.249, $p = 0.010$), but not significantly better than audio features-based model (t = 0.692, $p = 0.507$). We then calculated the feature importance of the best performed regressor to interpret our models. Previous study has calculated the feature importance to interpret the models constructed by random forest algorithm [5]. The importance value of each feature indicates the mean contribution of each feature in all decision trees. As shown in Figure 5, the audio features accounted for 76.50% of the models. As individual features, the perceived relaxed (6.39%) and happy (4.95%) emotions show important roles in sad music preference prediction, followed by Big Five personality factors and gender.

V. DISCUSSION AND CONCLUSION

Combining experimental psychology research methods and machine learning techniques, this research (a) investigated the effects of gender and Big Five personality factors on the preference for sad music in the Chinese social environment and (b) constructed sad music preference prediction models using audio features and individual features as inputs. Statistical analysis shows that males prefer sad music more than females do, and a significant interaction effect between gender and the extraversion factor is observed. The best-performing RFR model showed a low predictive effect on the preference for sad music ($R^2 = 0.138$), which may provide references for music recommendation systems. Finally, the feature importance-based model interpretation reveals that, in addition to the same music inputs (audio features), the perceived relaxation and happiness of music play an important role in the prediction of sad music preferences. In the statistical analysis, we also found that the perceived sad ratings are negatively correlated with music preference values, indicating that people generally do not like sad music. This result is contrary to previous findings. For example, Schubert found that the perceived negative valence of music was correlated with music preference [78]. There are three main differences between the work of [78] and our study. First, our study used Chinese pop songs, but the work of [78] used Romantic Western art music; second, none of our participants had received professional music training, but most of the participants in Schubert's experiment were musically experienced (having had music lessons for a long time); third, our study was conducted in the Chinese social environment, whereas the previous study was conducted in Australia. The differences in music inputs, individual factors, and social environment may be the cause of the opposite results. This also confirms the previous opinion that music preference depends on the ''musical environment'', ''cultural environment'', and the listener's characteristics [3]. Thus, we believe that the ''tragedy paradox'' of music only manifests itself in some people and in some situations.

Regarding the effect of gender on music preference, previous studies have shown that men gave higher preference ratings for more musical styles [33]. Our study proved that men have a greater preference for sad music than women do. North, Hargreaves, and Neill noted that music is central to men's identification with particular musical subcultures and self-presentation [75]. Self-presentational concerns play a significant role in men's musical taste [33]. Since sad pop music is a mainstream style in China, male participants showed a greater preference for sad music than females. For the Big Five personality factors, our findings are different from previous studies. The work of [69] found that openness to experience is positively correlated with sad music like ratings. However, our results showed no significant main effects of personality factors. One possible explanation for this is that the variations in personality structure in different countries result in differences in sad music preferences. Openness reflects the psychic structure and the need for experience [77]. The work of [69] was conducted by recruiting Finnish university students, while our work was conducted on a Chinese campus. Previous work has shown that Chinese people are significantly less open to experience than Finns [76]. Thus, the association between openness and music preference may also vary in different countries.

In fact, the constructed model does not show a good effect in predicting a preference for sad music ($R^2 = 0.138$), but it provides an indication as to the viability of the approach. This result is predictable. Because of the complexity of human beings, it is difficult to predict and explain human preferences by a few simple individual factors [11]. This study did find that individual factors and audio features can predict sad music preferences, which can provide some references for the cold start problem in music recommendation systems. We believe that by combining the item-user feedback matrix and our findings, music recommendation systems can be optimized, similar to previous studies using hybrid methods [79]. Thus, we suggest that more individual factors should be taken into account in future research.

Finally, several limitations of this study need to be noted. First, the audio features considered in this study were only subsets of the full information actually processed by listeners. Thus, more music features should be considered in future work, such as lyrics, music styles, perceived music traits, and other audio features [102], [103]; audio feature selection and processing methods can also be updated to achieve better results [13]; and the lack of musically meaningful features is also a pity of this study [103], [104]. Second, to ensure model interpretability, we selected the RFR algorithm to build the predictive model. However, when pursuing model effects, more flexible methods, such as convolutional neural networks and recurrent neural networks, can also be considered. The flexibility of methods is usually opposite to the interpretability of methods [20]. Third, this study applied PCA to conduct feature reduction, but this also removed some interpretability of audio features. Other methods, retaining more feature information, should be taken into account, such as the Relief and the forward and backward feature selection methods. Finally, the sample size of this study may be insufficiently robust to support a well preformed model. Since this study was conducted in a laboratory environment, collecting a large number of annotations may take considerable manpower and time. Future research should include online studies to collect more data. However, trade-offs still need to be made between the quality and the quantity of the data.

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