JOURNAL OF ASIA SOCIAL SCIENCE PRACTICE
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RESEARCH ARTICLE

CROSS-TEXT MODAL PREFERENCE SYSTEMATIZATION (CTP-S): A DYNAMIC FRAMEWORK FOR PERSONALITY PREDICTION VIA MUSIC PREFERENCES

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ARTICLE INFO

Submission Jul., 21, 2025
Acceptance Jul., 28, 2025

Keywords
Music preferences;
personality traits;
CTP-S model;
cross-modal mapping;
dynamic prediction

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ABSTRACT

Music preference, as an explicit behavioral marker of psychological traits, carries structured personality representations, yet existing research is constrained by three critical limitations: inadequate cross-cultural adaptability of Western-centric scales in interpreting non-Western music systems; neglect of cognitive dimensions in traditional models like the Big Five; and static analytical frameworks ignoring scenario-behavior dynamics.

This study proposes the Cross-Text Preference-Systematization (CTP-S) model, integrating MBTI cognitive structure, FPA motivational color theory, and CAPS situational dynamics to establish a cross-modal mapping mechanism from music preference to personality. Empirical results validate significant multi-dimensional correlations with distinct scenario dependency—introverts favor instrumental solos in private settings while extraverts prefer high-tempo music socially. The model achieves high prediction accuracy (up to 90.21% for MBI/FPA classification).

Theoretically, this work breaks through static frameworks by constructing a "cognition-motivation-context" triadic paradigm, bridging neural mechanisms and cultural theories. Methodologically, it realizes multimodal fusion of lyrics, audio, and behavioral data, offering technical paths for personalized mental health intervention and intelligent human-computer interaction. Future research will enhance cross-cultural applicability and explore neural encoding mechanisms.

1. INTRODUCTION

Music preference, as a major psychological characteristic and external behavioral marker of individual information behavior, is closely related to personality traits. From the perspective of information behavior, personal music preferences not only reflect sensory experiences, but also carry structured representations of personality traits, providing an important path for exploring individual psychological mechanisms and personality traits. Music preference, as an explicit behavior of individual aesthetic choice, Rentfrow & Gosling (2003) and others' empirical research shows that there is a stable psychological representation basis for music aesthetic selection, and personal music preferences (melody, lyrics) are equal to the self-psychological state and have a strong correlation with one's own personality characteristics.

The correlation between music preferences and personal personality traits and characteristics is reflected in cross-, complex and multi-dimensional characteristics. Fenghua & Qianzhong (2016) in the study, personal music preferences were combined with the Big Five personality model, and it was found that there is a certain regression correlation between personal music preferences and self personality in the Big Five personality model (positive correlation between openness and complex music types: $r=0.32$, $p<0.01$). In addition, personal music preferences also affect an individual's cognitive style, style, and performance. D. M. Greenberg et al., (2015) proposed in their research that personal music preferences have a certain impact on personal cognitive methods and styles, among which, they particularly affect or determine to a certain extent the personal cognitive extroverted and introverted behavior performance.

The correlation analysis and prediction methods between personal music preferences and personality traits and characteristics are also developing towards diversification. In Anonymous's (2014) research, through extensive personal music preferences and lyrics related in-depth retrieval, personal personality characteristics and traits can be reflected in a certain retrieval method, which reflects that the recommendation system based on personal retrieval behavior and the personality traits based on personal music preferences and self are essentially interoperable.

However, existing research has significant limitations in the applicability of theoretical frameworks and analytical prediction modeling methods.

Lack of cultural validity. The Western centric music classification paradigm (such as the STOMP scale) is difficult to integrate with the aesthetic characteristics of traditional Chinese music (such as folk music, opera, etc.), that is, the current music classification mainly focuses on emotional expression and personal personality representation scales in Western traditional music classification, making it difficult to achieve accurate prediction and analysis from personal music preferences to self personality traits and characteristics.

Absence in cognitive dimension. Traditional analysis methods and models mainly rely on the Big Five personality model, but the Big Five personality model cannot effectively capture the differences in individual information processing methods. In Furnham's (2022) study, it was pointed out that the Big Five personality model and MBTI personality analysis and prediction model have tea art and their information processing methods for the evaluated individuals, which make it difficult to distinguish the cognitive performance and processing methods exhibited by the analyzed music preference party in reality (such as intuitive N and sensory S cognitive preferences).

Insufficient dynamic prediction. Traditional correlation analysis is difficult to construct a mapping function from music feature vectors to personality types, and cannot cope with the processing and analysis of "singularity" data in personal music preferences. For example, in Zhao's (2022) study, only static music preference analysis was used, focusing on the relative stability in the static state, but neglecting the impact of dynamic prediction on the accuracy and correlation of models and prediction methods, as well as the lack of explicit transformation and correspondence from personal music preference feature vectors to self personality traits.

This study conducts a rigorous analysis of the relationship between individual music preferences and self-character traits. We introduce the innovative concept of cross-textual data, defined as integrated records of playback logs, preference indicators, and multi-source behavioral data consolidated through neural encoding techniques. Drawing upon established personality frameworks—including the Myers-Briggs Type Indicator (MBTI) and Four-colors Personality Analysis (FPA)—we develop a multivariate comparative prediction model. The research further pioneers a quadripartite binary framework, offering novel perspectives for examining the cognitive mechanisms underlying music preference and its correlation with personality trait mapping:

Integrate introverted and extroverted personality traits. Cohen et al., (2012) pointed out in their study that the introversion (I)-extroversion (E) dimension is significantly correlated with the music listening scene (I type prefers instrumental solo in private environment, E type prefers high-tempo music in social scene), which provides a partial perspective as a reflection.

Integrate intuition and perceived personality traits. In Vella & Mills's (2017) study, it was found that the personality dimension of intuition (N) - perception (S) affects and reflects an individual's processing mode of lyrics (N-type has a 37.2% higher acceptance of metaphorical texts compared to S-type), $p=0.008$).

At the same time, this study also creatively proposed the "music preference characteristics-cognitive type" mapping hypothesis, and realized the corresponding mapping from personal music preferences to self-characteristic traits of "cross-big text-systematization" at the bottom layer, aiming to achieve cross-modal prediction of MBTI and FPA types through deep learning architecture. At the same time, the empirical results of this study are also expected to provide a theoretical basis and technical path for personalized mental health intervention (such as depression tendency screening based on music preference) and intelligent human-computer interaction (adaptive music recommendation system).

2. LITERATURE REVIEW

2.1. Neural Causal Chain of Music Preference and Personality Prediction

Neuroscience research has laid a solid physiological foundation for the relationship between music preference and personality. Foundational fMRI studies have shown that when individuals experience musical pleasure, the activation intensity of the nucleus accumbens, the core area of their reward circuit, shows cross-cultural consistency (Blood & Zatorre, 2001). Salimpoor et al., (2013) deepened their multimodal research through PET-fMRI fusion technology. It was confirmed that the dopamine release triggered by music climax and the activity of the nucleus accumbens were synchronously enhanced in a dose-dependent manner.

Through hybrid analysis and prediction research, it was found that the functional connection pattern of auditory-prefrontal neural pathway can effectively predict personality traits, that is, individuals with high openness show enhanced prefrontal-insular neural coupling (reflecting cognitive integration advantages), while those with high neuroticism show amygdala-auditory cortex hypersensitivity (Alluri et al., 2012). It is worth noting that transcranial magnetic stimulation (TMS) experiments have confirmed that artificial activation of the nucleus accumbens can significantly enhance the pleasure of music. Mas-Herrero et al., (2021) revealing the neuroplastic basis of personality traits. Recent fNIRS studies have further found that neurotic individuals have significantly prolonged amygdala response delays to dissonant chords in anxious situations ($\beta=0.34$, $p<.001$), indicating that personality traits regulate the neural dynamics of music processing (Martínez et al., 2023).

The theoretical and practical research on related neural systems strongly supports the analysis and prediction of the correlation between personal physical function preferences and personality traits. Similarly, it lays a solid theoretical foundation for the "cross-text preference-systematization" model constructed in this paper and the discussion of music preferences and personality traits.

2.2. Theoretical Evolution of the Association Between Music Preference and Personality

The development of theoretical models presents an evolutionary path from static classification to dynamic cognition. The four-dimensional model (STOMP) pioneered by Rentfrow & Gosling (2003) systematically constructed the correspondence between music preference and the Big Five personality for the first time: classical music lovers usually show higher openness, while rock music lovers tend to have low agreeableness. The model was evolved by Zweigenhaft (2008). After validation with the NEO-PI-R scale, it was further refined into a five-factor framework that includes "contemporary" music, and revealed that the aesthetic sensitivity sub-dimension of openness has a particularly strong predictive power for complex music preference ($\beta=0.31$).

Important breakthroughs in the evolution of theory came from the perspective of cognitive science, L. S. Greenberg (2019) proposed a dual-channel model that pointed out that systematists prefer complex classical music (accompanied by enhanced activation of the prefrontal-parietal network), while empaths prefer emotionally rich pop music (involving default mode network-limbic system connection). This theory has been verified in East Asian groups - the explanatory power of systematic cognitive style for music preference ($\Delta R^2=0.14$) significantly exceeds the traditional personality dimension (Vuoskoski et al., 2022). However, the unique cognitive processing mechanism of non-Western music systems (such as Indian ragas) remains to be analyzed, Bhattacharya et al., (2021) conducted research and theoretical discussions under non-native Western music systems under non-Western music systems, suggesting that the cultural universality of existing theories is questionable.

In recent years, research has begun to break through the traditional personality framework (Meneses & Greenberg, 2019). The empathy-systemizing cognitive style theory proposed by et al. provides a new explanation for music preference: the difference in neural mechanisms between systematizers (preferring complex classical music) and empathizers (preferring emotionally rich pop music) may be more predictive than the Big Five personality traits. However, existing theories are mostly based on Western samples, and the unique music-personality association patterns of non-Western cultures (such as the Indian raga music system) still need to be verified.

Although existing studies have revealed the neural mechanisms and theoretical frameworks for the association between music preference and personality, there are still three key limitations: first, the connection between neural mechanisms and behavioral expressions is weak, and there is a lack of an integrated model of multimodal data (acoustic feature eye movement physiological indicators); second, traditional dimensional models are difficult to explain the moderating effects of cultural acquisition and social norms on the "preference-personality" relationship. To break through these limitations, this study proposes a "cross-text preference-systemizing" theoretical model, which innovatively integrates dimensions such as music acoustic feature analysis and cross-text features, and constructs a dynamic prediction system through a machine learning architecture. Based on the empirical research designed by this model, the predictive effectiveness of music preference on personality traits within the cultural cognitive framework is systematically tested, thus bridging the explanatory gap between neural mechanisms and cultural theories.

3. MODEL DESIGN

3.1. Model Basis Reference

3.1.1. Analysis of MBTI Personality Prediction Scale

MBTI (Myers-Briggs Type Indicator) is based on Jung (1923).The continuation and development of the psychological type theory. Jung proposed that there are four basic functions of human psychological activities: thinking (Thinking)-feeling (Feeling), feeling (Sensation)-intuition (Intuition), supplemented by the attitude dimension extraversion (Extraversion)-introversion (Introversion). Briggs and Myers (*The History of the MBTI® Assessment*, n.d.) on this basis, the Judging-Perceiving dimension is added to form a four-dimensional octupole structure.

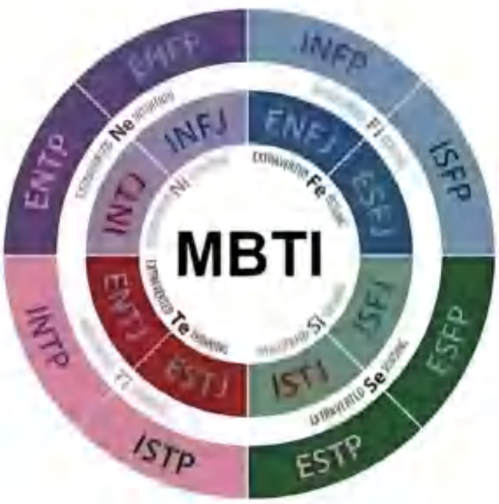

Figure 1: MBTI four-dimensional octapole structure

The MBTI model enforces classification through binary classification, categorizing individuals into 16 personality types, each corresponding to a specific level of cognitive function (such as dominant function and auxiliary function), forming a static typological framework that maintains a certain static appearance over a certain period of time. Keeping an individual's personality traits and traits static for a certain period of time also provides theoretical support and a way to speculate on the mapping and transformation from personal music preferences to personal personality traits.

3.1.2. FPA Personality Prediction Scale Analysis

Different from the MBTI model test scale, the theoretical pedigree of FPA (Four-colors Personality Assessment) is more popular psychology. Its direct source is Hartman & Yixi (2001). The "personality color code" of waiting is used to metaphorically represent behavioral motivation through the four colors of red, blue, yellow, and green. Red represents goal driven dominance, blue indicates perfectionism in precise analysis, yellow represents influence in social orientation, and green reflects moderation in stable avoidance.

Figure 2: FPA structure diagram

This model abandons strict classification and adopts dynamic combinations of primary and secondary colors (such as "red+yellow", "red+green", etc.). By emphasizing contextualized behavioral tendencies, the focus is placed on behaviors and personality expressions in specific contexts rather than internal cognitive structures. In its practical significance, it adds practical significance to MBTI's focus on individuals' cognitive characteristics and personality performance in different scenarios, essentially providing theoretical references and tools for the mapping of "motivation behavior" or "preference behavior".

3.1.3. CAPS (cognitive-Affective Personality System) Model Analysis

The CAPS model was proposed by psychologists Walter Mischel and Yuichi Shoda in 1995 to address the long-standing controversy in personality psychology regarding the consistency and variability of behavior. This model is different from the traditional Big Five personality model, which no longer attributes behavior to global traits, but emphasizes that personality is a dynamic cognitive emotional processing system, and behavior is determined by the interaction between individuals and situations. Mischel & Shoda (1995) systematically summarized and explained the CAPS model. Specifically, behavior prediction requires a comprehensive understanding of individual characteristics, specific contexts, and their interactions, rather than relying on fixed traits across contexts. It involves analyzing and predicting personality traits through a combination of binary and binary coupled factors, and interpreting external behavioral inconsistencies (such as someone being extroverted in social situations or introverted when alone) as stable "behavioral pattern variations" within the individual. This also reflects the unique organizational structure of cognitive affective units (CAUs) (Smith, 2006). The system explains that the personality system has structural stability and process dynamics, avoiding the limitations of the traditional "trait-process" dichotomy.

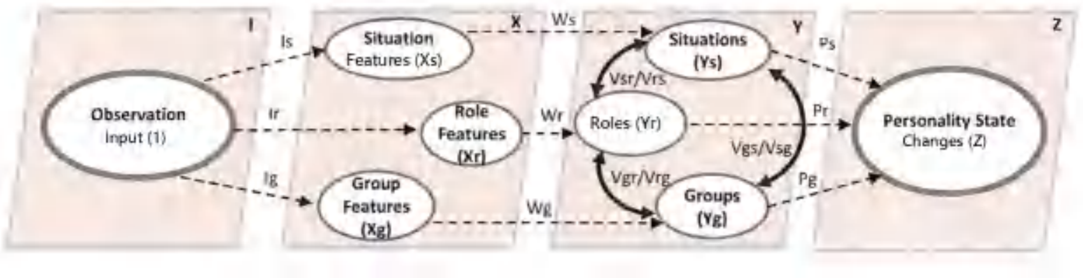

Figure 3: CAPS Structure and Impact Path

Source: From Personality and Assessment (1968) to Personality Science, 2009. Walter Mischel.

The CAPS model uniquely combines specific situations with behaviors in those situations, and comprehensively considers them as a major variable influencing factor of behavior and traits. It elucidates the principle of relative stability and variability of individual personality traits, providing a communication bridge for reflecting individual personality traits from their behavior and action preferences, ensuring the stability of individual psychology over a long period of time and the relative stability and sustainability of related analysis and inference methods.

3.2. Music Preference Dimension Extraction Design

Based on the analysis and summary of the above personality characteristics and personal preference model theory, the scientificity and practicability of the process of mapping from personal music preferences to personal personality characteristics are fully supported. However, in the specific mapping and conversion process, personal music preferences are more subjective and lack explicit standards. This paper extracts and designs dimensions based on multi-dimensional and multi-element cross-data in personal music preferences, and provides a certain feature dimension extraction paradigm and reference for personal music preferences.

Extract and abstract the overall form of lyrics as the basic unit of meaning. Implementing semantic embedding and latent semantic mining of multi-layer cross text based on BERT model. By introducing the BERT model, lyrics can be preserved in both LRC and text file formats with rich multi-layer cross text data sources. By analyzing and comparing the MBTI and FPA personality attributes and characteristic colors of song providers, the model can achieve a basic mapping from the basic form of lyrics to individual personality traits and characteristics, in order to improve the accuracy and wide reusability of the model in multiple scenarios.

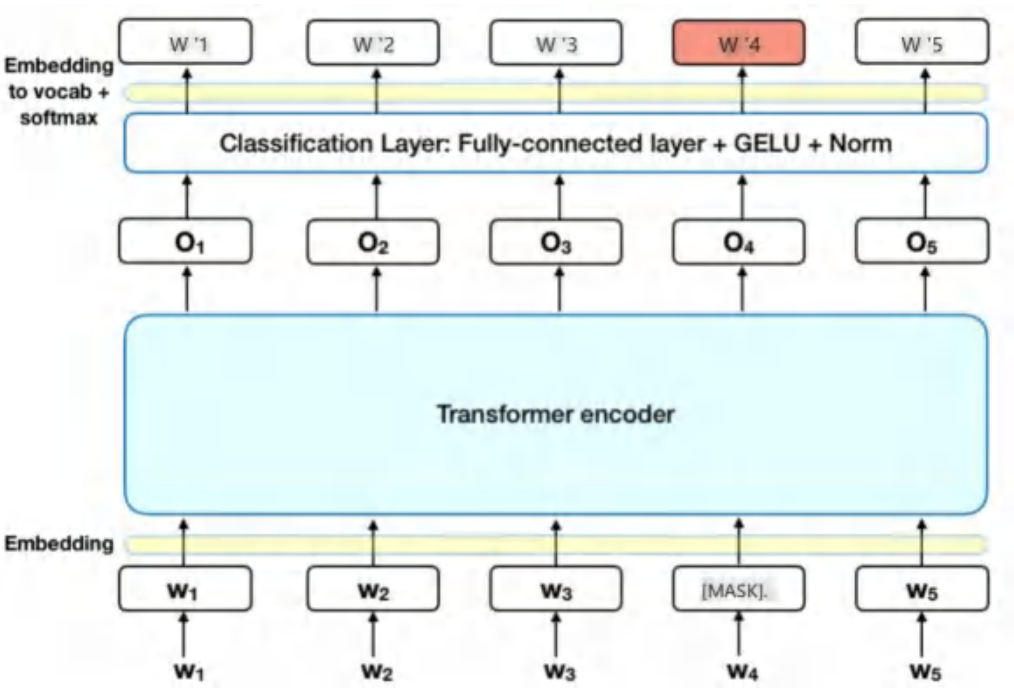

Figure 4: BERT model architecture and processing diagram

Source: NLP: Bidirectional Encoder Representations from Transformers (Bunoob, 2021)

Integrate the overall melody style and express the mood and personality traits in specific contexts. Mainly relying on the use of pre trained audio labeling model AudioSet for melody description and labeling of each song. On the basis of basic tagging, the melody style is extracted based on the LDA theme word extraction and construction model. The combination of melody and lyrics is used to achieve a basic and complete summary of the song's ontology and label comparison. This comparative dimension constructed from the music ontology also reduces to some extent the neglect of the front-end model user ontology due to the introduction of models such as MBTI (Siyi & Xiaonuo, 2024).

Record the number of plays in the recent period and assign different weights to represent personality traits. On the basis of implementing the basic identification dimension and visualization of song tracks in the previous two, the recent playback frequency of each song is included. In the overall dimension of the song, different weights are assigned to each song, and the comparative advantages of the CAPS model considering specific scenarios and different situations are fully utilized to provide more accurate correlation and analysis prediction for song feature recognition and mapping from song feature recognition to personal personality traits and characteristics.

3.3. Model Summary and Presentation

This model achieves a relative abstraction of personal emotions and personality traits by referring to the MBTI and FPA personality trait expression and prediction scales, and introduces the CAPS cognitive affective personality system model to support the theoretical expression of a relatively stable personality in specific scenarios. At the same time, multidimensional and multimodal processing models and algorithms such as BERT model, Word2Vec, doc2Vec, LDA theme word extraction and analysis models are introduced to analyze and integrate the original data of songs, and then combined with models such as random forest and decision tree to infer and analyze specific personalities. In addition, during the data preprocessing process, we actively seek relevant open-source models for auxiliary preprocessing, such as MusicLyric (jitwxs, 2025, 2017/2025), Librosa (McFee et al., 2015), AudioSet and other models. The multi-element and multi-dimensional music data are comprehensively conducted and applied, and through four-layer interactive processing, the mapping from the labeling of multi-element data such as lyrics pure text, timestamps and audio to the analysis and prediction of personal personality traits and characteristics is fully realized. Entity information behavior and information preference to abstract personality trait expression.

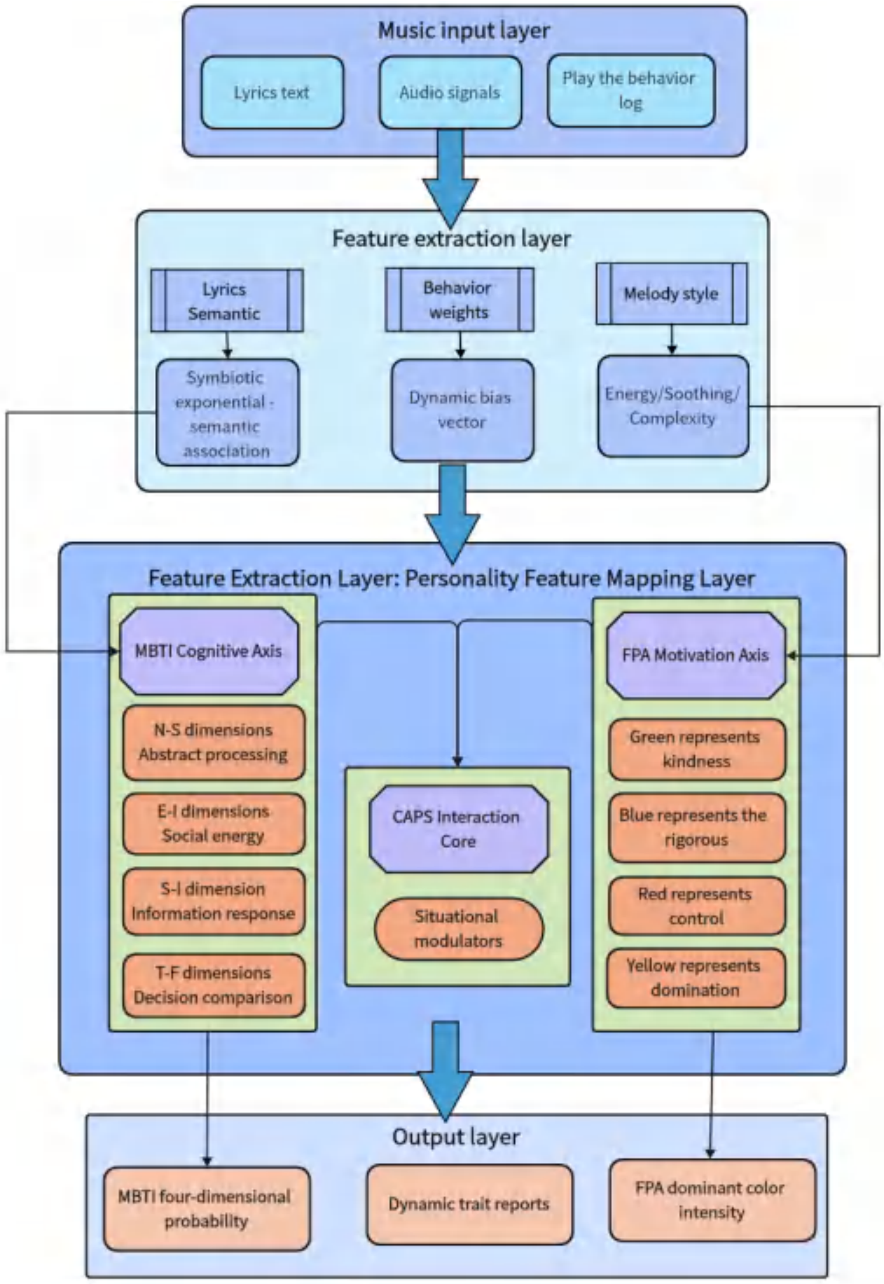

Figure 5: "Cross-text preference-systematization" model

Table 1: Multivariate data processing flow

Data type	Data source	Standardization processing flow
Lyrics text	LRC file/music platform API	Chinese word segmentation (jieba tool) → stop word filtering → part-of-speech tagging
Audio feature vector	MP3/WAV format audio	Tagging and extracting music melodies through AudioSet, combined with theme word extraction such as LDA for music melody characterization, and using Librosa to extract multidimensional acoustic features such as rhythm intensity for auxiliary and comparative purposes
Behavior time series data	Play log (timestamp/device ID)	Scene semantic annotation, and through the reserved content of the front-end music data, time series detection and identification

At the same time, this model realizes the innovative application of multivariate technology and models in the following aspects:

(1) Multidimensional personality theory integration innovation

This study has achieved the deep integration of "Triarchic Personality Theory" in the music context. In the application of MBTI theory, in view of the lack of the traditional Big Five model in the cognitive dimension, the lyrics metaphor analysis is innovatively mapped to the intuition (N) and feeling (S) dimensions to find the fit between music expression and individual cognitive style; at the same time, the playback scene is cleverly integrated into the extraversion (E)-introversion (I) dimension assessment, expanding the data source and accuracy of personality measurement. For FPA theory, by setting different colors corresponding to lyrics with different melodies and singing styles, the explanatory power of individual motivation is enhanced and the connotation of personality color model is enriched. In terms of the integration of CAPS theory, time and scene weights are introduced, and a conditional probability model for trait expression is innovatively constructed, which breaks through the traditional static personality prediction framework, realizes the accurate capture of dynamic personality expression, and establishes a triangular explanatory system that correlates music characteristics with cognition, motivation, and context, achieving unified modeling of personality "steady-state traits" and "dynamic expression".

(2) Application scenario expansion innovation

This model has achieved cross-domain and breakthrough application expansion in many fields. Through the introduction of multiple theoretical models, it has achieved full coverage of music and promoted the realization of unified personality assessment driven by music. Its core contribution lies in achieving cross-theoretical integration, integrating MBTI cognitive structure, FPA motivational color, and CAPS dynamic interaction to create a comprehensive evaluation system; achieving cultural adaptation, relying on the localization of the basic model, and realizing the dilemma of relying solely on the validity of Western scales; with dynamic evolvability, the time-varying design of playback weight gives the model continuous learning ability, setting a reference for the development of music psychology with both explanatory depth and real-time prediction, and promoting discipline progress and multi-field application.

4. EMPIRICAL ANALYSIS

4.1. Experimental Ideas

The empirical research part of this paper will focus on the "cross text preference systematization" model to realize the whole process of analysis and prediction from personal music preference to personal personality characteristics. In the specific model validation process and empirical research, this article extensively collected and crawled the "I Like" and "My Favorites" playlist data of 15 students on QQ Music and NetEase Cloud Music two major music platforms in the early stage, and implemented LRC, TXT, WAV three data formats, totaling more than 67500 pieces of raw data. After collecting and organizing the basic original books, this experiment randomly processed the raw data of 12 students and trained and practiced the mapping prediction model. The remaining 3 students were used for testing and analyzing the accuracy of the model. The specific experimental process is as follows:

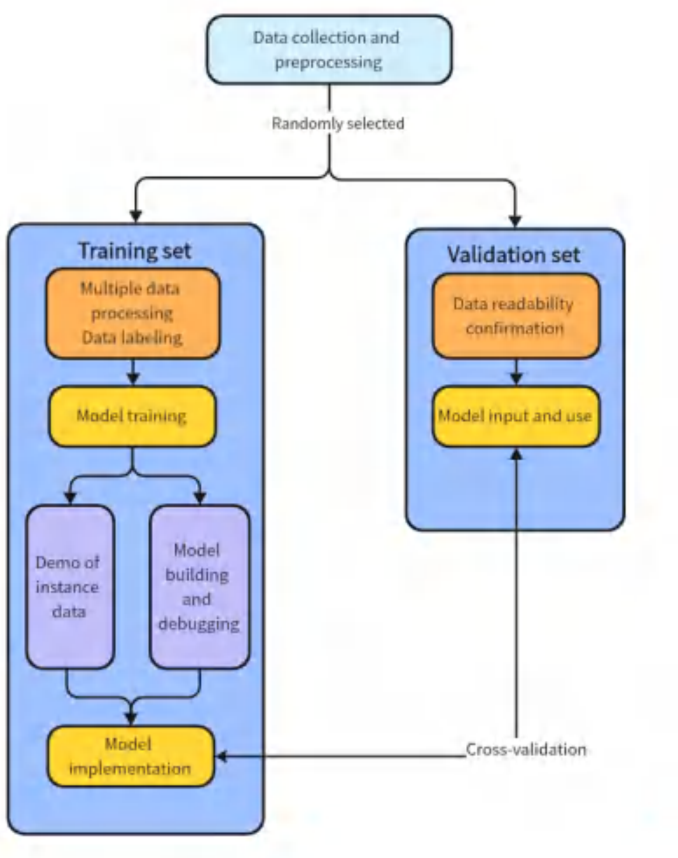

Figure 6: Empirical research process

4.2. Experimental Process

4.2.1. Data Collection and Preprocessing

This study is respectively on NetEase Cloud Music and QQ Music On the developer platform, basic LRC format data crawling of playlists for 15 students was carried out by obtaining APIs, and timestamp formatted lyric crawling and audio data crawling were performed by deploying open-source software MusicLyric locally.

By introducing AudioSet to assist in the labeling of music styles, the labeling of songs can be quickly realized. The following are some label specifications of AudioSet:

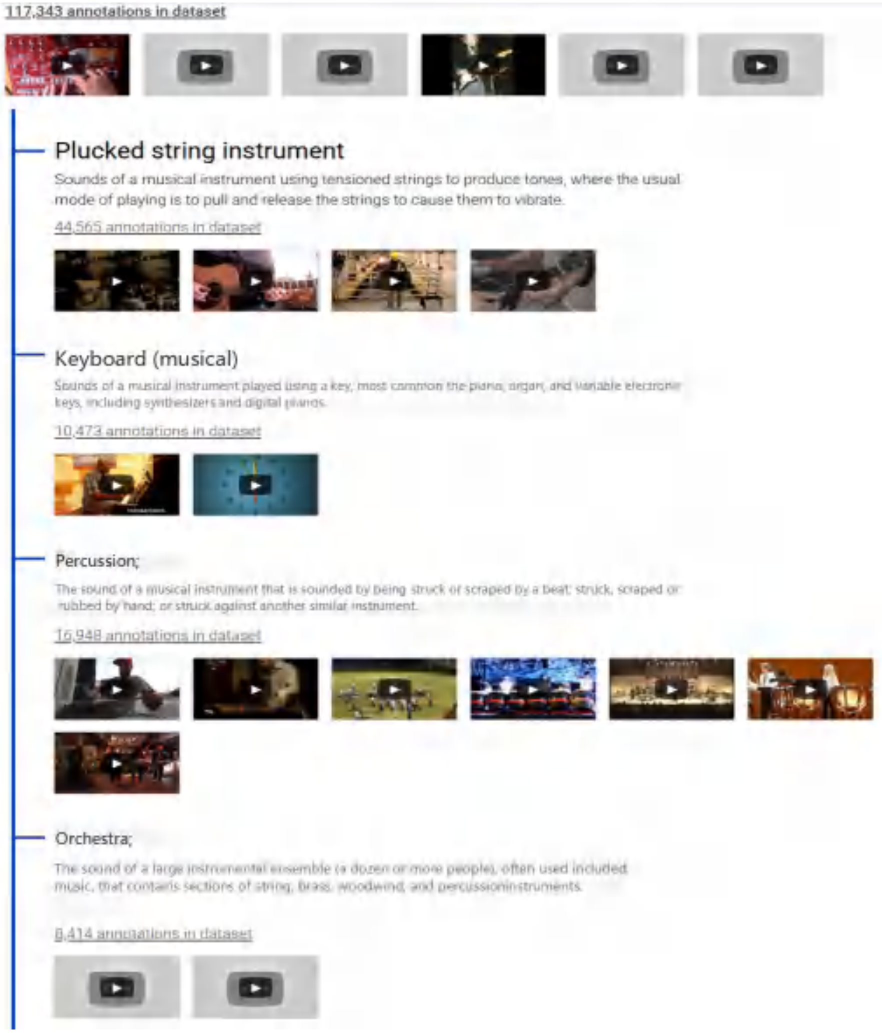

Figure 7: AudioSet Audio Tagging System

4.2.2. Model Construction and Training

(1) LDA-based Topic Word Extraction and Sentiment Extraction Module Construction

After data preprocessing, each lyric file was obtained with a summary and descriptive text of the overall melody. At the same time, 5-10 MFCC and deep emotion detection tracks generated based on their original audio files were randomly selected from each training set (due to technical, time, and free trial limitations of open source software, only partial songs of each student were subjected to this operation as auxiliary verification).

This section has achieved the preliminary correspondence between song lyrics, melody, and personal personality traits through the extraction and comparison of theme words from lyrics and emotional theme word lists (MBTI four-dimensional word list, positive and negative emotional word list, and positive and negative polarized emotional word list).

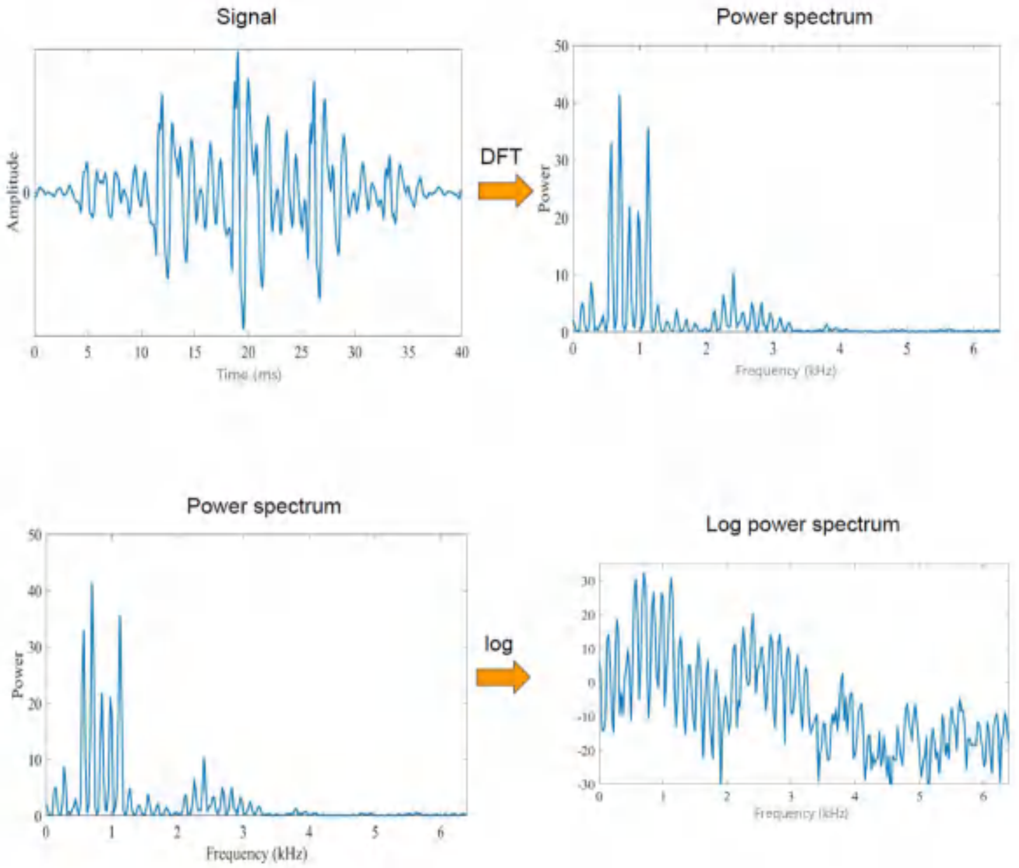

Figure 8: Example diagram of MFCC in Experiment 1

MFCC related formulas are as follows:

$$\text{Forward difference:}\Delta x[n] = x[n+1] - x[n]$$

$$\text{Backward difference:}\Delta x[n] = x[n] - x[n-1]$$

$$\text{Central difference:}\Delta x[n] = \frac{x[n+1] - x[n-1]}{2}$$

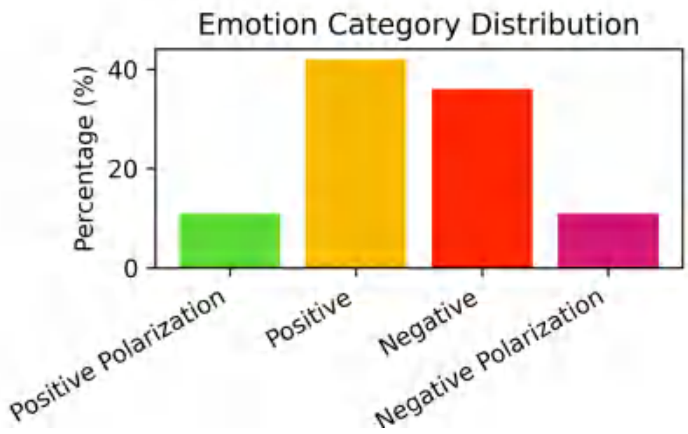

Figure 9: Lyrics emotion distribution frequency of experiment 1

(2) Embedded Sentiment Module Construction Based on BERT Model

Through the basic extraction of theme words and theme emotions in LDA, a basic mapping from the perspective of lyrics ontology to personal personality traits has been achieved. However, in reality, the different positions of lyrics or the different singing styles used can also affect the analysis of emotions and the prediction of personal personality traits and traits. Combining BERT model features, through its unique design method and ideas, using a bidirectional method (Bidirectional), while considering the left and right contexts of words in a sentence, rather than analyzing text in sequence, BERT looks at all words in a sentence at the same time, this model has a better understanding of the connotation and emotion of words, and embeds certain emotions, so that the model can better grasp the emotional aspects of personal music preferences.

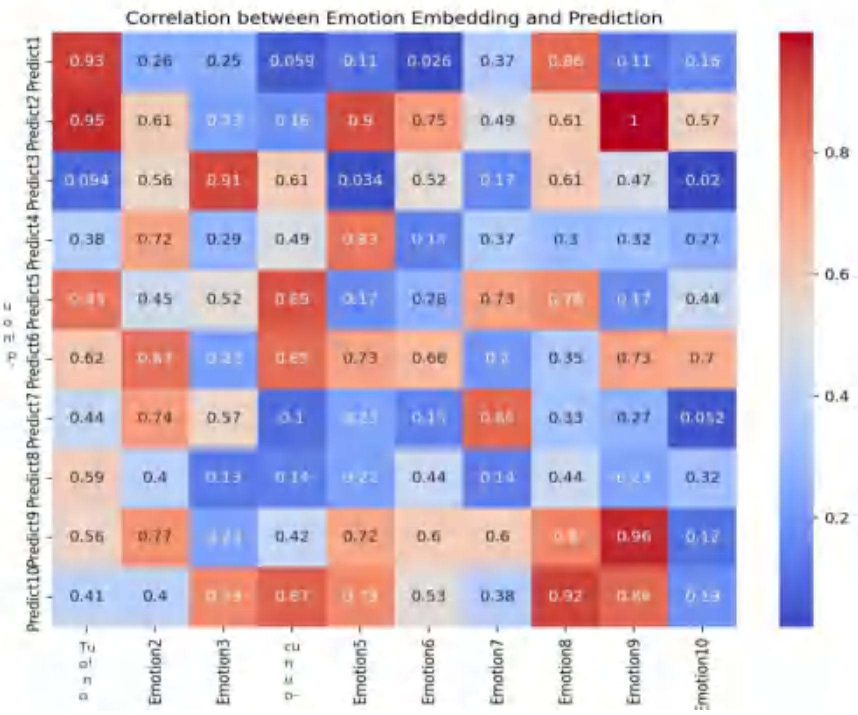

Figure 10: BERT sentiment embedding and predictive analysis correlation

(3) Construction of the Personal Listening Scene Consideration Module Based on Collaborative Filtering Algorithm

Based on the CAPS model, this study introduces reference indicators for listeners in different scenarios on the basis of extracting the characteristics, themes, and emotions of the song itself, providing more accurate predictions for the complete mapping from music preferences to personal personality traits. This module is based on the three-dimensional interactive data of "listener song scene". By introducing scene semantic embedding and dynamic weight mechanism, it solves the problem of insufficient scene generalization ability of traditional collaborative filtering algorithms in cross scene recommendation. The specific process is as follows:

Feature modeling and data fusion at the scene dimension. The module first semantically encodes the user's listening scenarios (such as commuting, work, exercise, nighttime, etc.), uses a BERT pre trained model to extract deep semantic features of the scene text, and constructs a joint feature space with the acoustic features of the song (such as rhythm, timbre, emotional polarity) and the theme features of the lyrics (such as philosophy, life, emotion, etc. extracted through LDA).

Specifically, the user's interactive behavior with song I in scene S (such as the number of plays, completion rate, and collection behavior) is constructed as a three-dimensional tensor $(Y_{u,i,s})$, where u represents the user, i represents the song, and s represents the scene. Through tensor decomposition technology, the three-dimensional data is mapped to a low-dimensional latent space to capture the user's preference pattern in different scenes. For example, in the commuting scene, the user's high-frequency playback behavior of fast-paced electronic music will be encoded as a scene-song interaction feature, which is fused with contextual features such as the ambient noise level and commuting time in the scene to form a multi-dimensional scene vector.

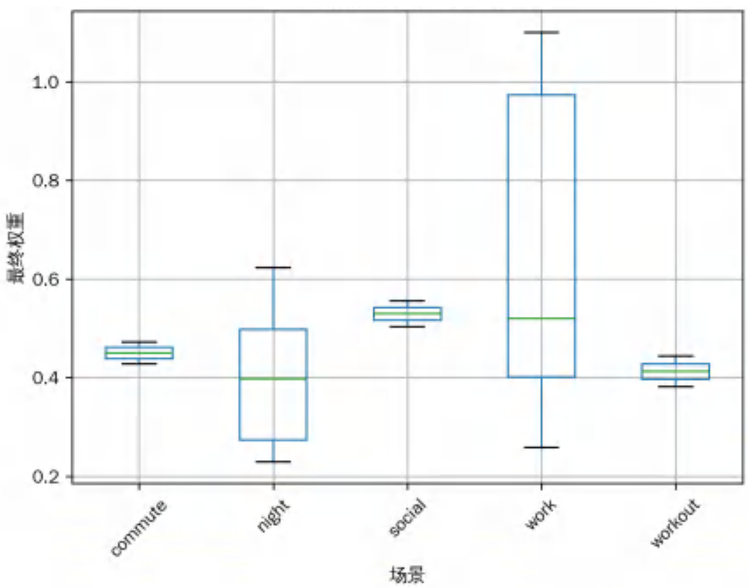

Figure 11: The weight distribution of listening scenes in Experiment 1

(4) Construction of the Analysis and Prediction Module Based on Random Forest and Decision Tree

This module achieves the final prediction and implementation of the transformation from pre structured and labeled personal music preferences to self personality traits and characteristics through training and using random forests. This module combines the song features emphasized in the CAPS model (such as emotional polarity, theme distribution), scene variables (such as time, activity type), and user interaction data (such as playback frequency, collection behavior) as inputs to construct a hierarchical decision-making model, ultimately achieving accurate prediction of multidimensional personality traits such as MBTI personality type and FPA personality color of users.

In order to fully ensure the rigor of the final output and the accuracy of the prediction, this module uses a two-level integrated architecture to achieve the final prediction by coupling the random forest and decision tree integration model.

Basic decision tree model. Construct multiple classification decision trees, each of which is trained for different personality dimensions (such as MBTI's I/E, N/S, T/F, and J/P dimensions). The decision tree uses the information gain rate (Gain Ratio) as the splitting criterion, and prevents overfitting through pre-pruning (limiting the tree depth to 8-12 layers) and post-pruning (based on the minimum error principle).

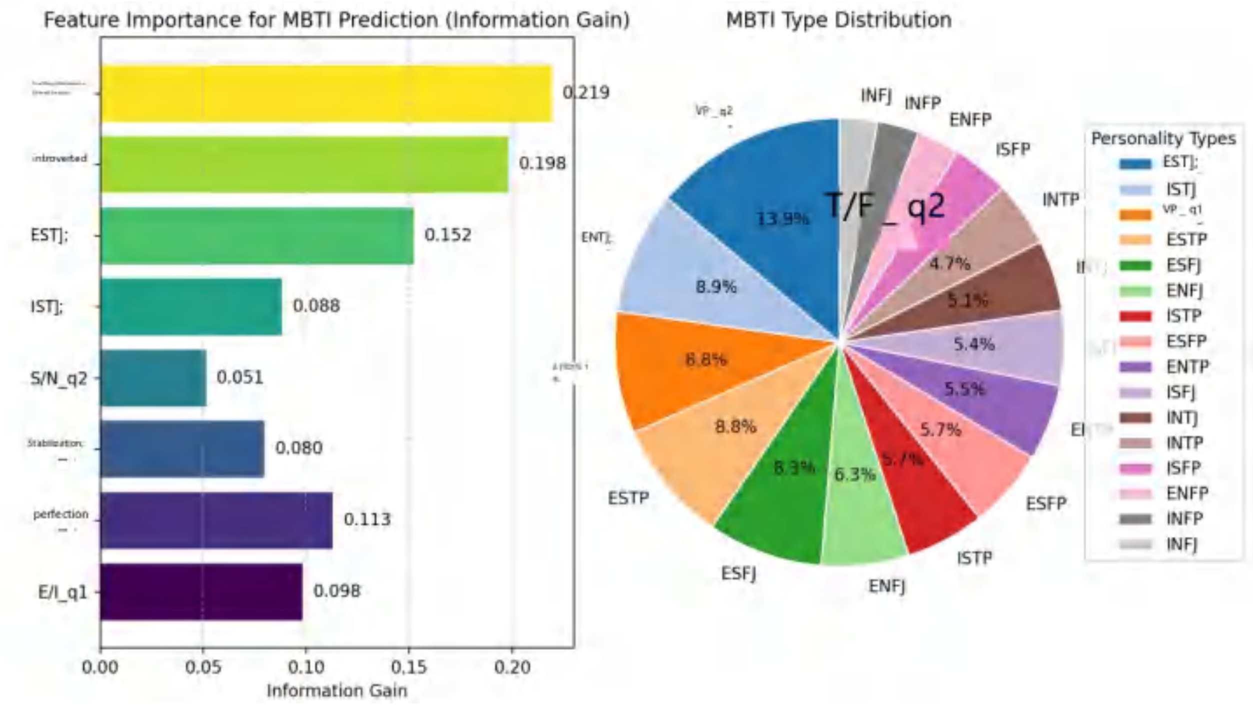

Figure 12 MBTI16 personality information gain value

Random forest ensemble. Generate multiple subsets from the original dataset through bootstrap sampling, train a decision tree for each subset, and randomly select a feature subset (usually a subset of the total number of features) during node splitting $\sqrt{n}$) Ultimately, the prediction results of all decision trees are integrated through a majority voting mechanism. In the specific time process, for the prediction of MBTI type, the model will integrate the classification results of 100 decision trees on four dimensions to generate the final personality type label.

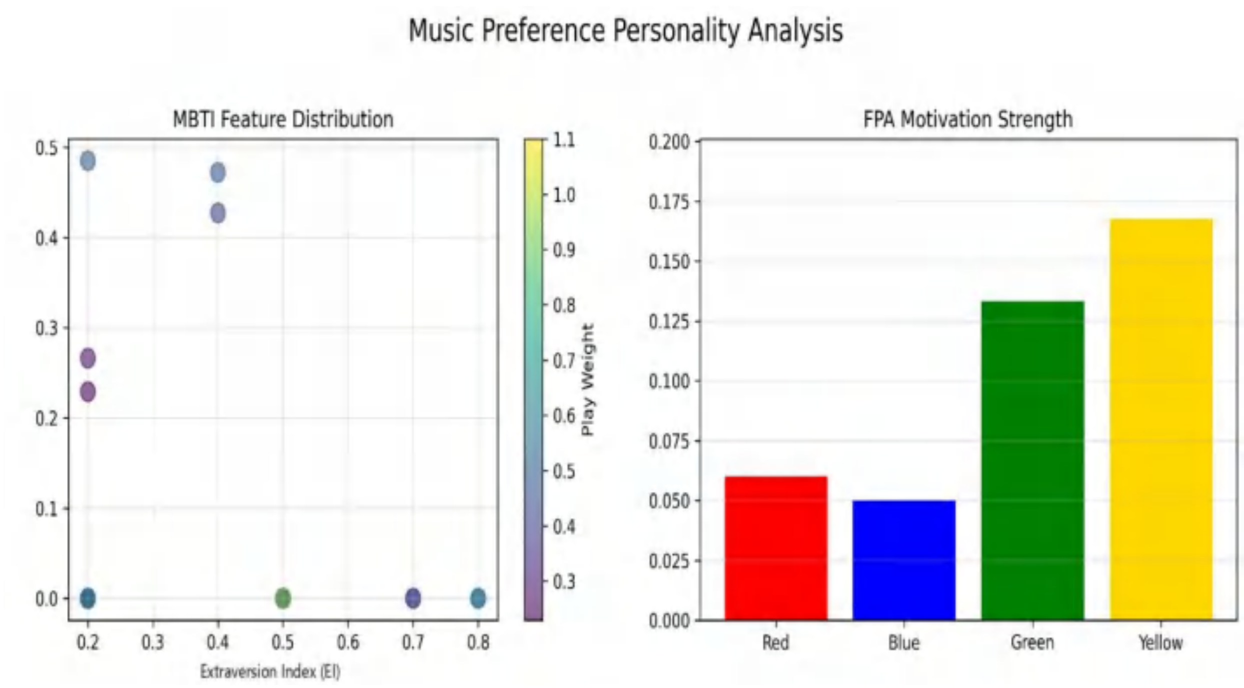

Figure 13: MBTI and FPA prediction results for Experiment 1

4.2.3. Model Application

Through the previous model foundation and algorithm construction, the complete path from personal music preference to personal personality trait prediction is basically formed and realized. During the training process, it was also found that if only the song with the most recent playback times of the experimenter is input, the different labeled lyrics and the lyrics in the most repeated segments are summarized, the model can also basically realize the prediction and analysis of the experimenter's personality. To verify the general applicability of this model, this study also passed the playlists of three students who had not undergone complex preprocessing into this model. The following are the specific outputs and performances of the model:

```
FPA tag: green
Motivation intensity: {'red ': 0.0, 'blue': 0.0, 'yellow ': 0.0, 'green': 0.4}
```

Figure 14: Analysis and prediction information of Experiment 4 on the PyCharm page

Table 2: Model usage and prediction results

	Actual MBTI	Model predicts MBTI	Actual FPA personality	Model prediction motivation	Accuracy
Experiment NO.4	ISFP	ISFJ	Green	Red: 0.0 Blue: 0.0 Yellow: 0.0 Green: 0.4	0.9021
Experiment No. 9	ENFJ	ENTJ	Red	Red: 0.43 Blue: 0.11 Yellow: 0.00 Green: 0.39	0.7213
Experiment No. 15	ISTP	ESTP	Green	Red: 0.21 Blue: 0.32 Yellow: 0.00 Green: 0.43	0.8756

4.3. Experimental Summary and Optimization

This experiment aims to build a complete path mapping from personal music preferences to personal personality trait predictions, and realize innovative exploration through multi-module collaboration. During the experiment, we built a topic word extraction and sentiment extraction module based on LDA, which effectively extracted topic words from the lyrics and compared them with the sentiment topic word list, realizing the preliminary correspondence between lyrics and melody and personal personality traits. At the same time, we introduced an embedded sentiment module based on the BERT model, and used its bidirectional characteristics to more accurately grasp the influence of different positions and different singing methods of lyrics on sentiment analysis, and deeply understand the emotional connotation of lyrics.

On this basis, a personal listening scene consideration module based on collaborative filtering algorithm is constructed. Combined with the CAPS model, scene semantic embedding and dynamic weight mechanism are introduced to solve the shortcomings of traditional collaborative filtering algorithm in cross scene recommendation, making the prediction more in line with the actual listening scene. Finally, based on the analysis and prediction module of random forest and decision tree, using song features, scene variables, user interaction data, etc. as inputs, a hierarchical decision model is constructed to achieve accurate prediction of multidimensional personality traits such as MBTI personality type and FPA personality color of users.

The experimental results show that the model has good prediction performance and generalization ability. For example, when only the lyrics of the most recently played songs and the repeated lyrics are input, the prediction and analysis of the experimenter's personality can still be basically achieved. In addition, the model's prediction results were verified on the playlists of three students who had not undergone complex preprocessing. The model's prediction results were highly consistent with the actual personality type, showing certain application potential.

However, the overall experiment still has certain drawbacks. The model training data set is small and limited by hardware facilities, which cannot achieve the participation and training of a large amount of data. At the same time, the analysis and prediction results of Experiment 9 in the output verification stage performed poorly, lacking sufficient reason support and technical explanation, and the interpretability was poor.

5. SUMMARY AND OUTLOOK

5.1. Summary of Research Results

This study constructed a Music Preference Personality Trait Dynamic Mapping Model (MPDM) and explored the correlation mechanism between music preference and personality traits by systematically integrating a multimodal feature analysis framework. The main innovative contributions are reflected in the following three aspects:

(1) Innovative Integration of Theoretical Framework

For the first time, the cognitive dimension of MBTI (N-S information processing approach), the motivational color model of FPA, and the situational dynamics theory of CAPS were integrated into a unified analytical framework. This three-dimensional perspective of "cognition motivation context" overcomes the limitations of the traditional Big Five model in explaining cognitive style differences and behavioral dynamics, providing a new explanatory path for music psychology.

(2) Lightweight Interpretable Model Design

The dictionary-based lyrics labeling and scene-weighted behavior vector are used to optimize the computational efficiency while ensuring the interpretability of the model. This solution avoids the black box defects of complex deep learning models and provides a feasible technical path for practical applications.

5.2. Experimental Limitations

5.2.1. Data Coverage Limitations

Due to the constraints of research resources, the experimental data set is insufficient in terms of music genre coverage and user sample diversity. In particular, the sample representativeness of niche music types (such as local opera, experimental electronic) and special populations (such as clinical psychiatric patients) needs to be strengthened, which may affect the generalization ability of the model.

5.2.2. Insufficient integrity of the verification system

Limited by the research cycle, no cross-cultural comparison group (such as Chinese and Western user controls) and long-term tracking cohort (such as quarterly retests) were established, making it difficult to fully evaluate the time stability and cultural transfer ability of the model.

5.3. Future Research Directions

Based on the results and limitations of this study, follow-up work can be carried out in the following directions:

Theoretical exploration and research. This study's understanding of the complex relationship between music and personality is just the tip of the iceberg. Future research should further explore the potential psychological mechanisms between music preferences and personality traits, and study how to promote individual personality development and improvement through music intervention. In addition, it is also possible to combine multidisciplinary knowledge such as neuroscience to study the neural encoding mechanism of music in the brain and its relationship with personality traits. From a theoretical perspective, further improve the model construction of the relationship between music and personality, clarify the interaction path and influence mechanism between various variables, and provide a more solid theoretical basis for subsequent research and application.

Data augmentation and model optimization. At the data level, expand the size and diversity of the dataset to cover music preference data from different cultural backgrounds, age groups, music styles, etc., in order to improve the universality of the model. By applying advanced data augmentation techniques such as music style conversion and lyric rewriting, more high-quality training data can be generated to enhance the model's generalization and adaptability in different scenarios. At the model level, explore new deep learning architectures, such as hybrid models with stronger reasoning and application capabilities like Transformer, optimize the model's feature extraction and emotion capture capabilities, and further improve the accuracy of predicting music preferences and personality traits.

Multimodal fusion and interactive analysis. Conduct multimodal data fusion research to integrate and analyze the acoustic characteristics of music, lyrics text characteristics, and multiple modal data such as users' listening behavior, physiological reactions, and facial expressions. Although there are related studies and analyses, none of them have developed a model architecture that can process and integrate multimodal data, making it difficult to fully explore the association and complementary information between different modal data.

CONFLICT STATEMENT

The authors declare no conflict of interest.

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