Sustainable Development Using Deep Learning and Big Data Analysis: Innovative Development of Music Events and Cultural Tourism

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Abstract: This work aims to achieve innovative development of Xiamen's music events and cultural tourism through deep learning (DL) and big data analysis (BDA) methods, all while prioritizing sustainable development. In today's pursuit of green, healthy, and sustainable growth, Xiamen has established new requirements for local music activities and the cultural tourism industry. Specifically, there is a need to adopt innovative approaches that ensure the sustainable growth of these sectors by leveraging the potential of big data. Firstly, data on music activities and cultural tourism from 2018 to 2022 is analyzed in detail. DL structures, such as convolutional neural networks and recurrent neural networks, are used for feature engineering to extract the temporal and spatial characteristics of music activities and cultural tourism data, fully displaying the correlation between music preferences and the regional economy. Relevance judgment and correlation analysis methods are also applied to confirm the relationship between users' music preferences, Gross Domestic Product (GDP), and per capita disposable income in different regions. Secondly, DL models such as multi-layer perceptrons and deep neural networks are employed. These models are trained on large-scale datasets and optimized to simulate the complex relationship between music choices and regional economic indicators. The trained DL model is then utilized for correlation assessment and analysis to explore higher-order relationships within the data, providing profound insights for the sustainable development of music activities and cultural tourism. The results show that the DL-based approach can accurately predict music preferences and reveal the complex and subtle interactions between music choices and regional economies. These findings offer a new approach and perspective for Xiamen to construct an innovative music tourism industry chain and promote the sustainable development of the local economy. The analysis reveals that the diversity of music choices is negatively correlated with GDP and per capita disposable income, while the diversity of user music preferences is positively correlated with both. Therefore, combining the diversity of musical activities with the regional uniqueness of cultural tourism can achieve mutual promotion and common development. The DL-based approach accurately predicts users' music preferences and reveals the subtle interplay between music choices and the regional economy. Furthermore, the innovation of this work lies not only in validating the correlation between musical activities and economic development but also in proposing a new model that tightly integrates music events with cultural tourism development. This provides a scientific basis and practical guidance for constructing an innovative music tourism industry chain in Xiamen. This work introduces novel concepts and methodologies aimed at facilitating the establishment of an innovative music tourism industry chain in Xiamen, thereby fostering local economic development. While this work has made some progress in verifying the feasibility of the method, the specific types of local music festivals that can be developed in Xiamen have not been listed in detail. Future research should explore the specific impact of different music genres on the attractiveness of cultural tourism and how to more effectively integrate local cultural characteristics and musical activities to promote sustained regional economic growth.

Keywords: music events; cultural tourism; characteristic industrial chain; sustainable development; users' music preferences; deep learning

1. Introduction

In the context of contemporary society's pursuit of green, healthy, and sustainable development, Xiamen has established new criteria for local music events and the cultural tourism industry. This involves embracing innovative approaches to achieve sustainable development in both sectors by leveraging the potential of big data. The current emphasis on the development of music events integrated with big data focuses on several key aspects: selecting event themes, crafting compelling topics to attract tourists, and deeply implementing the principles of sustainable development. Through platform externalization and data analysis, the construction of cultural tourism is intricately woven into every aspect of music competitions. This approach fosters a distinct tourism culture unique to Xiamen's music events and solidifies a robust cultural identity.

There is a profound understanding and significant progress in the current research on music events and the cultural tourism industry. De Sancha Navarro and Lara (2021) utilized neural networks to explore the sustainability of foreign music culture [1]. Melpignano (2019) argued that world heritage sites could be protected by hosting music events and other activities, which could enhance local tourism characteristics by exploring new opportunities [2]. Domestic scholars have identified that the development strategies for

digital music events and the cultural tourism industry represent a dual imperative in the current era and market landscape. Music must be integrated with digital communication platforms and methods to establish novel channels of communication, thereby effectively leveraging its role and advantages [3, 4]. Concurrently, music digitization, referred to as the music industry in the context of big data, can substantially augment its diversity by catering to intergenerational differences [5]. Additionally, Li (2023) proposed the digital inheritance and development of music in the big data era, asserting the necessity of leveraging new technologies to discover novel avenues for the sustenance and development of music [6]. Moreover, it is recognized that the proliferation of various digital platforms necessitates corresponding adaptations in music events [7]. The latest viewpoints suggest that music events should embrace challenges with an innovative approach, thereby instilling fresh vigor into the landscape amidst the tide of sustainable development [8]. Especially in cities where tourism is a cornerstone industry, music tourism emerges as a sector with promising economic returns [9]. Developing music events and integrating them with the tourism industry is conducive to achieving cultural confidence, better developing regional characteristics, and promoting local culture. Notably, the development of cultural tourism centered around music themes facilitates the establishment of a strong tourism brand. At a regional level, increasing tourism cultural highlights, attracting tourist resources, and promoting characteristic activities are complementary. This innovative form fosters the tourism development of music and cultural resources, achieving a win-win situation for the culture and tourism industries. Regarding research on the innovation and development of music competitions, Zhang et al. (2023) [10] discussed how to protect the intangible cultural heritage of ethnic minority music in Yunnan Province through innovative methods. They analyzed the challenges facing ethnic minority music in Yunnan, such as cultural assimilation and the impact of modernization, and proposed a series of strategies to protect and revitalize these musical traditions. These strategies encompass educational outreach, community engagement, and dissemination using modern technologies, enhancing the sustainability of these musical forms and facilitating their transmission in contemporary society. Dong et al. (2023) [11] studied the spatial distribution of intangible cultural heritage in the Guizhou Province of China and its impact on tourism competition. Through empirical analysis, the study revealed the potential of intangible cultural heritage in promoting local tourismprogress. It also pointed out the competitive relationship between different regions in the use of cultural heritage. The study highlighted the importance of rational planning and management of intangible cultural heritage resources to achieve sustainable tourism development. Gocer et al. (2024) [12] proposed a framework to analyze the influence of cultural tourism on the resilience of rural communities. Using case studies, the research showed how cultural tourism can help rural communities increase their resilience to external shocks. Through the development of cultural tourism, new economic opportunities could be provided to rural communities while preserving and passing on local cultural heritage. Pinglan et al. (2024) [13] investigated the symbolic interaction and meaning change of Mazu culture in the coastal city of Fujian Province, China, in the context of world cultural heritage. By analyzing the socio-cultural background of Mazu belief and its evolution in modern society, they discussed how cultural heritage can maintain its vitality and relevance amidst globalization and modernization. The study emphasized the significance of developing a deep understanding of cultural heritage and respecting its role in contemporary society. Papadaki (2024) [14] used Greece as an example to study the synergistic effect between green tourism and cultural and creative industries. The research explored the potential synergy between sustainable tourism and the preservation and enhancement of local cultural values by integrating these two domains. A set of policy recommendations was formulated to foster a mutually beneficial scenario wherein economic growth is coupled with cultural preservation. This is achieved through the promotion of green tourism and the cultural and creative industries.

Currently, there is a lack of research addressing the innovative advancement of music events and cultural tourism industries within the framework of sustainable development in Xiamen. This work utilizes data from NetEase Cloud Music, employing big data as a foundational tool to analyze the characteristics of music development. It comprehensively examines and consolidates the use of big data in music events, proposing a sustainable innovation model that aligns the trajectory of music event development with that of the cultural tourism industry. The goal of this research is to provide practical recommendations for Xiamen to establish a distinctive tourism industry chain.

2. Innovative model for music event development and cultural tourism development

2.1 Explanation of the concept of music events and cultural tourism

Music events serve as platforms where musicians participate in concentrated competitions and convey musical aesthetics to the public. Beyond showcasing talents, these events also define aesthetic frameworks in music appreciation [15]. The taxonomy of music competitions is intricate, encompassing diverse categories based on varying standards. Typical categories include vocal performances, instrument solos, and ensemble performances, further classified into world-class, continental, national, provincial, and other scales [16]. Music events are characterized by their extended duration, distinct styles, diverse activities, significant cultural elements, and high participation rates, making them large-scale, clustered competition activities.

Cultural tourism refers to the process of perceiving, understanding, and experiencing specific aspects of human culture through travel [17]. Broadly defined, it includes journeys aimed at appreciating the traditional cultures of different countries and regions, exploring the legacies of notable figures, or participating in local cultural activities. Cultural tourism enriches tourists' intellectual horizons and fosters a spirit of exploration, while also developing and promoting local cultural characteristics, extending the cultural and spiritual dimensions of tourism [18]. The cultural tourism industry leverages regional disparities as catalysts, viewing the interaction and intersection of diverse regions and cultures as ongoing processes. It emphasizes the harmonious coexistence of cultures

as a desirable outcome, encompassing consumption content with broad implications and profound significance [19]. Cultural tourism activities are characterized by their regional specificity, artistic richness, captivating allure, diverse offerings, and interactive engagements. These activities serve as crucial mechanisms and strategies to promote and expand local culture, ultimately creating a cultural brand effect [20].

2.2 Current status of music event development and cultural tourism development in the context of big data

2.2.1 Integrating music event development with big data: a case study of NetEase Cloud Music

Music events play a crucial role in shaping the cultural tourism industry chain in Xiamen. Effectively cultivating compelling themes for music events is essential for enhancing cultural tourism. Therefore, understanding the specific developmental processes of these events is paramount. Figure 1 illustrates the development process of music events.

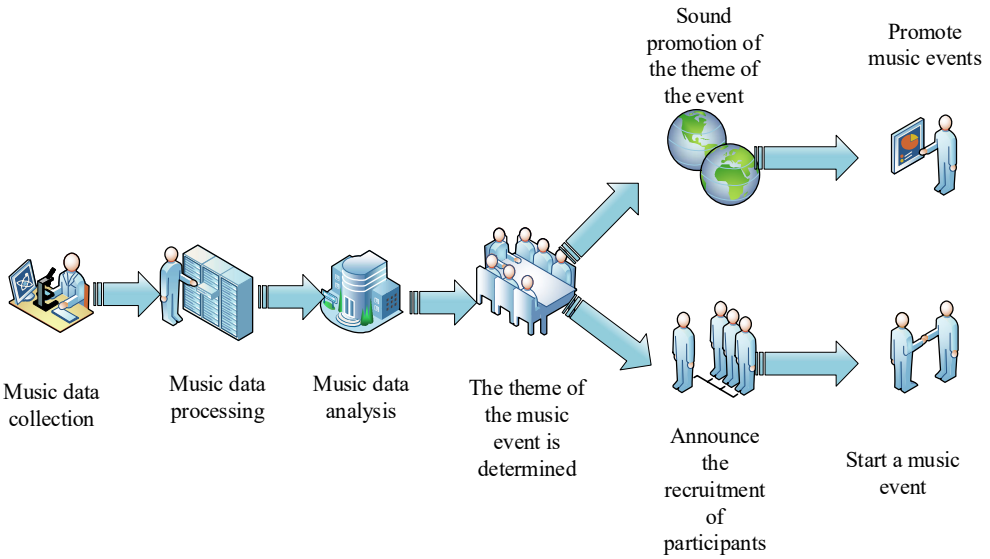

Figure 1 Development process of music events

Figure 1 illustrates the comprehensive considerations involved in developing and hosting music events. The chosen theme dictates the overarching musical motifs of these events, serving as the cornerstone of music competitions. Big data plays a crucial role in identifying regional music preferences and guiding the development of music events. Additionally, big data facilitates other stages of event development, including data analysis and external promotion. This section utilizes data from NetEase Cloud Music to examine the topic selection process in music event development [21].

Since its launch in April 2013, NetEase Cloud Music has amassed tens of millions of registered users, making it one of China's largest online music platforms. A dataset comprising 30,562,590 playlist samples, representing approximately 10% of the total, is captured. Table 1 presents details of the information contained within these playlists.

Table 1 Main fields and their meanings of NetEase Cloud Music sample playlists

Field	**ID**	**User ID**	**Province**	**City**	**Tracks**	**Name**	**ID**
Data type	Int	Int	Int	Int	Array	String	Int
Meaning	Favorite playlist ID number	User ID	The code of the user's province	The code of the user's city	Information for each song in the playlist	The name of the song	Song ID
Owning field		creator	creator	creator		tracks	tracks

The research focuses on the playlists from NetEase Cloud Music, specifically the Favorites playlist selections, referred to hereafter as Favorites playlist. In this context, ID denotes the identifier for the user's Favorites playlist, name refers to the playlist's title, creator

encompasses details about the creator (including age, gender, and nickname), and tracks list the song names and their respective IDs within the favorites.

The data processing process is outlined as follows:
Step 1: The dataset of favorite playlists is read. User IDs are extracted from the creator field, and song IDs are extracted from the tracks field. Each song ID and its corresponding user are collected and stored in a file.
Step 2: User information is then analyzed to match each user with their geographical location, enabling region-based queries.
Step 3: Song information is gathered where each song ID is paired with its corresponding music style label, facilitating easy queries of song attributes.
Step 4: Finally, all collected data undergo analysis based on the above processes. This work explores differences in music preferences across diverse regions and user demographics, highlighting regional and user diversity perspectives.
The specific algorithm is outlined as follows:
Assume $p(g)$ represents the probability density of the random variable G. Equation (1) defines the entropy for G.

$$E(G) = -\sum_{g} p(g)\, log_2\, p(g) \tag{1}$$

For music i, the entropy E_i^N of regional distribution information for the audience is described using the function p_{ij}. Here, p_{ij} denotes the relative proportion of users of music i within the total audience in region j, as shown in Equation (2).

$$E_i^N = -\sum_{j} p_{ij} \log(p_{ij}) \tag{2}$$

The relative proportion p_{ij} is derived from Equation (3):

$$p_{ij} = \frac{q_{ij}}{Q_j} \left(\sum_{r} \frac{q_{ik}}{Q_k} \right)^{-1} \tag{3}$$

In Equation (3), q_{ik} and Q_k represent the number of listeners and users in region k, respectively. Equation (4) defines the regional diversity C_i^N of the audience for music i.

$$C_i^N = \frac{E_i^N}{\log(X)} \tag{4}$$

In Equation (4), X denotes the total number of regions. A value of 0 for C_i^N indicates concentrated music audience in a region, while a value of 1 indicates dispersed audience, reflecting the entropy of the distribution.
Next, the regional diversity index of any region y is defined as the average regional diversity across all individual users within that locality:

$$C_y^N = \frac{\sum_l C_l^U}{Q_y} \tag{5}$$

$$C_l^U = \frac{\sum_n^{L_l} C_m^M}{Q_y} \tag{6}$$

Here, C_l^U represents the individual regional diversity of user l, reflecting the average regional diversity across all music in the user's Favorites playlist; L_l denotes the length of the Favorites playlist, indicating the number of songs. A higher final regional diversity index signifies a greater prevalence of commonly favored music genres among regional users, suggesting widespread interest in these music types. Conversely, a lower diversity index indicates a higher concentration of attention on popular music genres, implying a relatively smaller and more focused audience for these genres.

The range [0,1] is utilized to denote the definition range of regional diversity, divided into X intervals. Equation (7) defines the personal preference diversity C_i^P for user i.

$$C_i^P = \frac{-\sum_j v_{ij} \log(v_{ij})}{\log(X)} \tag{7}$$

In Equation (7), v_{ij} represents the regional diversity in songs within the j-th interval. Equation (8) describes the proportion v_{ij} in user i's Favorites playlist music:

$$v_{ij} = \frac{d_{ij}}{D_{ij}} \left(\sum_{y} \frac{d_{iy}}{D_y} \right)^{-1} \tag{8}$$

In Equation (8), d_{iy} denotes the number of songs with regional diversity falling within the j-th interval in user i's Favorites playlist. D_y is the total number of such songs across all users' Favorites playlists falling within the j-th range. A value closer to zero indicates more concentrated regional diversity, while a value closer to one suggests a more uniform distribution.

This work utilizes average preference diversity entropy to effectively capture individual musical style preferences by quantifying the regional diversity of music within a user's Favorites playlist. Entropy serves as a metric to assess users' music preferences: high entropy indicates a broad interest in music genres popular among the general population, while low entropy suggests a preference for niche music styles with smaller, more dedicated audiences. A playlist with evenly distributed music styles across regions approaches an entropy value of 1, indicating diversified music preferences. Conversely, concentrated preferences in specific regions result in lower entropy values approaching 0, indicating a more uniform preference. Thus, this work provides valuable insights into the diverse music preferences of users, offering a foundation for personalized recommendations tailored to music events and cultural tourism initiatives.

2.2.2 Development of music events and sustainable development of the cultural tourism industry

The primary objective for advancing music events and the cultural tourism industry is to achieve sustainable development [22]. Current research on sustainable music development primarily focuses on the preservation and perpetuation of traditional music [23]. However, this work explores the use of big data and integrates the development of music events with cultural tourism to create a distinctive tourism industry chain [24]. Consequently, it is essential to propose feasible strategies for developing Xiamen's unique cultural tourism industry chain. Through comparative literature analysis, this work examines the relationship between music genres, cultural imprints, and cultural beliefs [25]. Sustainable development principles are deeply embedded in the development of music events and cultural tourism, emphasizing the formation of distinct cultural identities through branded cultural experiences [26]. Future pathways for the development of music events and cultural tourism are envisioned through the preservation and continuation of ethnic music within the framework of sustainable development principles [27].

2.2.3 Integration of music event development and cultural tourism

The integration and evaluation of cultural tourism across diverse regions emphasize the need for Xiamen's music events and cultural tourism to embody distinctive and externally recognizable cultural characteristics and identities. For instance, regions like Tibet have developed "red tourism" by merging patriotic education with the tourism industry [28]. Similarly, cultural tourism characteristic towns have been established in Sichuan Province, and characteristic rural tourism initiatives are flourishing in Jiangsu Province [29, 30]. Therefore, to provide valuable recommendations for the advancement of music events and the cultural tourism industry in Xiamen, it is crucial to delineate a sustainable development path that integrates music events and cultural tourism in alignment with Xiamen's unique attributes through comprehensive literature analysis.

2.3 Extraction of music events and cultural tourism data based on deep learning

To achieve the research objectives, an advanced method that combines deep learning (DL) and big data analysis (BDA) is employed. Initially, relevant data from 2018 to 2022 concerning Xiamen's music events and cultural tourism are gathered, including user music preferences, regional Gross Domestic Product (GDP), and per capita disposable income. The collected data undergo rigorous cleaning and preprocessing using DL techniques to eliminate noise and outliers, thereby ensuring the accuracy and reliability of the dataset.

To comprehensively explore the insights embedded within music events and cultural tourism data, DL models are employed for feature engineering and representation learning, enabling richer and more abstract feature expressions. Convolutional neural network (CNN) architectures are utilized to focus on extracting spatial features from the music events and cultural tourism data. Through convolutional operations, the model automatically captures variations in music preferences and cultural tourism characteristics across different regions, thereby enhancing its understanding of regional influences. For time-series data related to music events and cultural tourism, recurrent neural network (RNN) structures are introduced to capture temporal variations. RNN, known for its ability to retain information over time, effectively handles time-series data, thereby uncovering dynamic correlations between music preferences and regional economies and providing depth to the model's insights. The outputs from the CNN and RNN models are integrated to form a comprehensive feature representation. This integration enables a holistic depiction of the spatio-temporal relationships within music events and cultural tourism data, thereby enhancing the modeling capabilities concerning the association between user music preferences and regional economic indicators. The algorithmic process for extracting spatial features from music events and cultural tourism data using the CNN structure is detailed in Table 2:

Table 2 Algorithm process of spatial feature extraction based on CNN

```
#Use CNN to extract the spatial characteristics of music events and cultural tourism data

# Step 1: Data preprocessing
data_matrix = normalize_data(data_matrix)

# Step 2: Define the CNN model structure
model = Sequential()
model.add(Conv2D(num_filters,kernel_size=filter_size,activation='relu',input_shape=in-
put_shape))
model.add(MaxPooling2D(pool_size=(2, 2)))

# Step 3: data reconstruction
model.add(Flatten())

# Step 4: Add Full Connection Layer
model.add(Dense(dense_units, activation='relu'))
model.add(Dense(output_units, activation='softmax'))

# Step 5: Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

```
# Step 6: Model training
model.fit(training_data, labels, epochs=epochs, batch_size=batch_size)

# Step 7: Feature extraction
features = model.predict(data_matrix)
```

The CNN-based structure is utilized for extracting spatial features from music events and cultural tourism data. The algorithm is outlined in seven steps:

1) Data Preprocessing: The data undergoes normalization processing to ensure compatibility with the CNN model input.
2) CNN Model Definition: The CNN architecture is defined, comprising convolutional and pooling layers designed to automatically capture nuances in musical preferences and cultural tourism characteristics across diverse regions.
3) Data Reconstruction: The output from the convolutional layers is flattened into a one-dimensional vector.
4) Fully Connected Layer Addition: A fully connected layer is added for feature classification.
5) Model Compilation: The model is compiled, specifying the optimizer and loss function for training.
6) Model Training: Training of the model occurs using the specified training data and corresponding labels.
7) Feature Extraction: Post-training, the model is used to extract spatial features from music events and cultural tourism data.

This structured approach enables the extraction and representation of spatial features critical for understanding the dynamics between music events, cultural tourism, and regional preferences.

Compared with other state-of-the-art algorithms, the algorithm proposed in this work innovates by integrating DL and BDA, making it particularly suitable for processing and analyzing complex data in the music and cultural tourism domains. Utilizing the CNN structure, the model autonomously learns data patterns, eliminating the need for manual feature extraction, which proves highly effective for handling large-scale datasets. Moreover, the model design incorporates the correlation between music preferences and regional economic indicators, shedding light on the economic and cultural factors influencing users' music choices. This approach provides robust data support for the innovative development of cultural tourism. The method holds significant application value at the intersection of music and cultural tourism, offering a scientific foundation for strategy formulation and optimization within related industries.

Concurrently, meticulous consideration is given to capturing the intricate relationship between music preferences and regional economic indicators through the selection of multilayer perceptron (MLP) and deep neural network (DNN) models. The MLP model processes input data, incorporating abstract feature representations from the feature engineering and representation learning stages. With its multilayer architecture, the MLP model discerns and models complex nonlinear relationships between music preferences and regional economic indicators. Furthermore, the introduction of DNN enhances the model's depth, increasing sensitivity to potential correlations in the data. By employing multiple hidden layers, the DNN effectively learns abstract hierarchical feature representations, comprehensively revealing the underlying connections between music preferences and regional economies. Training procedures utilize a comprehensive dataset encompassing music events and cultural tourism data, ensuring the model's proficiency in capturing complex data patterns. This work iteratively optimizes model parameters to maximize fitting capability on the training data. Such iterative refinement ensures the accuracy and robustness of the model in subsequent correlation assessments and analyses.

3. Research results

3.1. Data analysis of music event development model

3.1.1. Statistics on the regional diversity of music preferences

During the data collection process, comprehensive data from all provinces in China is gathered, sourced from the official website of the National Bureau of Statistics. The dataset includes national statistical figures for 23 provinces, 4 municipalities, 5 autonomous regions, and 2 special administrative regions for the year 2022. This dataset encompasses a wide array of indices such as national accounts, population demographics, employment statistics, energy consumption, financial indicators, and more. Specifically, GDP, per capita GDP, and per capita disposable income for each region are queried and utilized as part of the analysis. The entropy value reflecting user diversity in music preferences and local GDP in each province is derived from an examination of the Favorites playlists of NetEase Cloud Music users, as depicted in Figure 2.

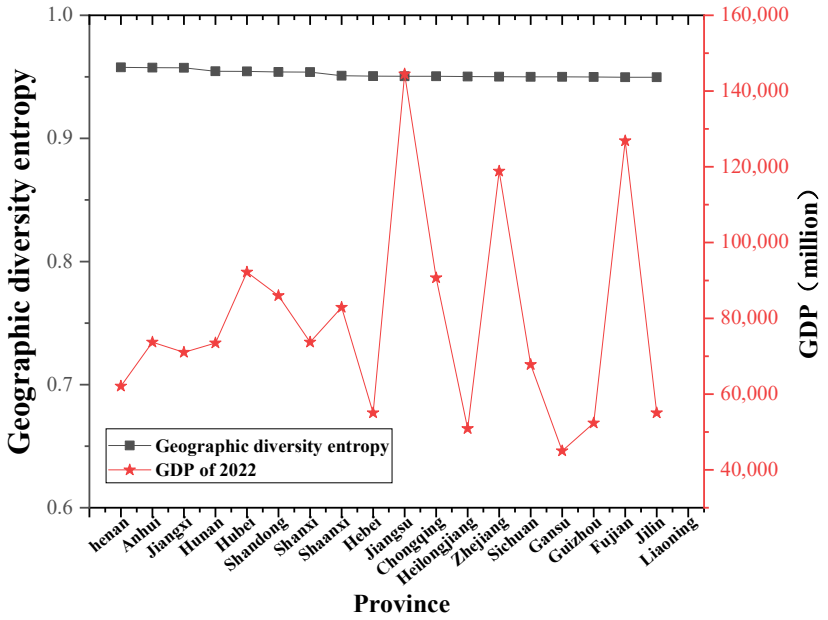

Figure 2 Entropy value of regional diversity and local GDP in 2022 of music preferences among users in different regions (unit: 10,000 CNY)

Meanwhile, the relationship among average regional diversity, local per capita GDP, and per capita disposable income can be observed in Figures 3 and 4. These visual representations highlight a significant negative correlation, with a correlation coefficient r of -0.743 and a significance level P=0.0000479.

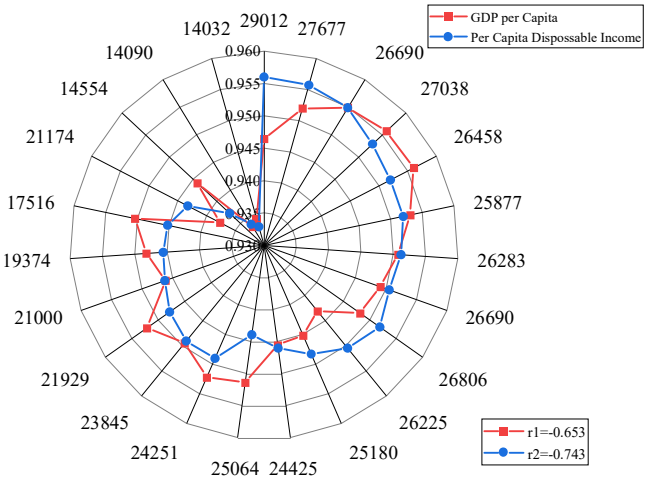

Figure 3 Correlation between average regional diversity of users' music preferences and GDP and per capita disposable income (correlation coefficients: r_1=-0.653, r_2=-0.743)

Figure 3 illustrates that the average regional diversity of users' music preferences exhibits an inverse relationship with both per capita GDP and per capita disposable income. Specifically, this inverse association is more pronounced with per capita disposable income, suggesting that regions with stronger economies tend to exhibit greater diversity in the music preferences of their residents.

3.1.2 Diversity and similarity of users' music preferences across regions

The diversity of regional user preferences is assessed using novel indices designed to quantify the range of musical preferences across different regions, providing insights into their diversity. Figure 4 illustrates the average preference diversity of users in each region alongside the per capita disposable income for the year 2022.

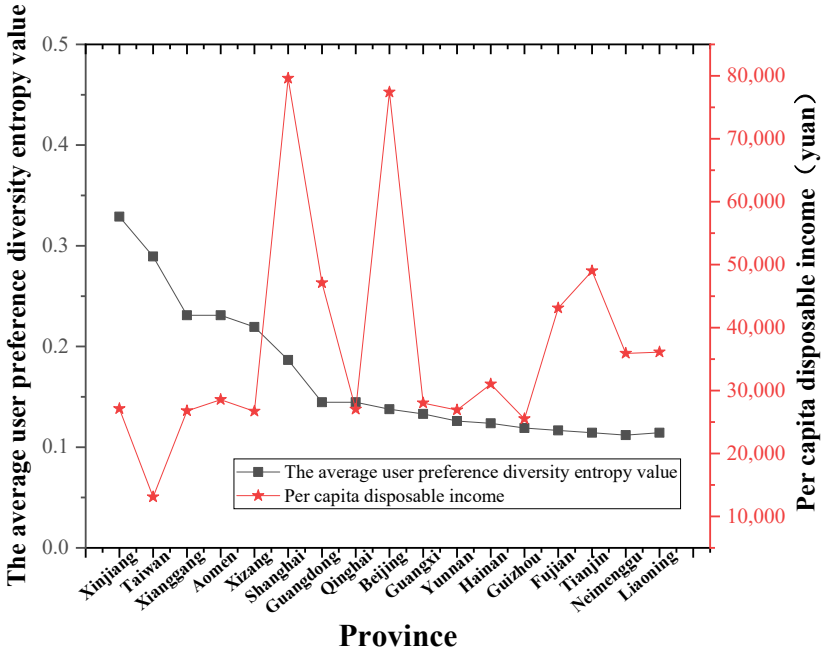

Figure 4 Entropy of average preference diversity of users in the region and local per capita disposable income in 2022 (Unit: CNY)

An analysis of the correlation between the diversity of average user preferences across various regions and the per capita GDP and per capita disposable income is presented in Figure 5. The correlation coefficients are 0.620 and 0.711, respectively, with significance levels of 0.0016 and 0.000143. These findings highlight that in economically developed regions, people tend to have diverse musical preferences, with actual income levels playing a significant role in shaping users' musical choices.

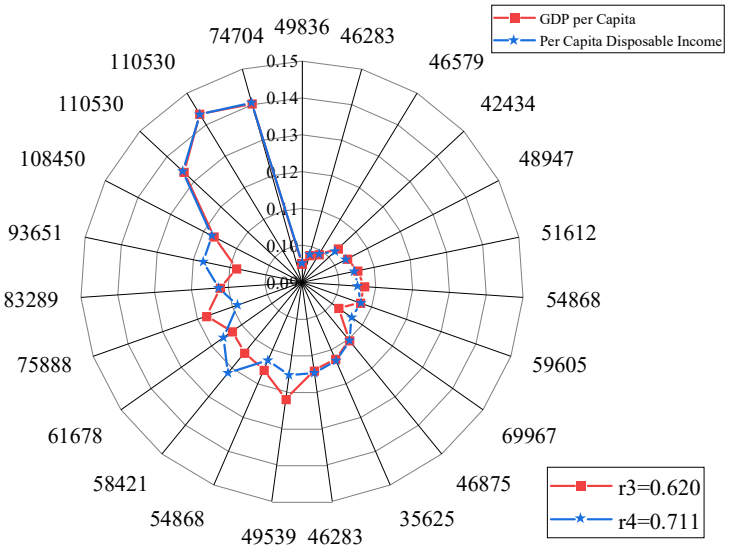

Figure 5 Correlation between user average preference diversity and GDP and per capita disposable income (correlation coefficients r_3=0.620, r_4=0.711)

Figure 5 highlights a direct correlation between the diversity of user preferences and GDP, with a more pronounced relationship observed between user preferences and disposable income. This trend suggests that regions with stronger economic foundations tend to show broader musical inclinations, encompassing a diverse array of genres and styles.

Table 3 illustrates the GDP performance of Fujian Province from 2018 to 2022, highlighting Xiamen's position as the third-ranking entity in terms of GDP. This economic standing correlates with local users exhibiting a heightened propensity for diverse music preferences. When formulating music event themes, integrating local characteristics while emphasizing sustainable development can effectively target specific domains, thereby enhancing tourist attraction and engagement.

Table 3 GDP of Fujian Province from 2018 to 2022 (Unit: 10,000 CNY)

Years/City	2022	2021	2020	2019	2018
Fuzhou	12308.23	11324.48	10020.02	9472.30	8516.09
Quanzhou	12102.97	11304.17	10073.66	9903.66	9019.24
Xiamen	7802.66	7033.89	6435.02	6015.04	5468.61
Zhangzhou	5706.58	5025.40	4557.61	4686.83	4368.15
Ningde	5334.62	3151.08	2577.00	2541.70	2194.43
Longyan	3314.47	3081.78	2778.90	2678.96	2400.53
Putian	3116.25	2882.96	2633.97	2545.39	2374.03
Sanming	3110.14	2953.47	2689.19	2601.56	2354.40
Nanping	2211.84	2117.58	1957.40	1991.57	1817.97

The process of determining themes for the progression of music events in Xiamen can be guided by the aforementioned data. Of particular note is the strong correlation observed between user music preferences and per capita income levels. When combined with local characteristics, this correlation can lead to the development of music event themes that carry profound significance and strong appeal.

Furthermore, the development of innovative music events requires a forward-looking approach to analyze Xiamen's development trends in the coming years based on big data. Figure 6 elucidates the total GDP and GDP change trend of Xiamen City over the past five years, while Figure 7 illustrates the per capita disposable income and its variations during the same period.

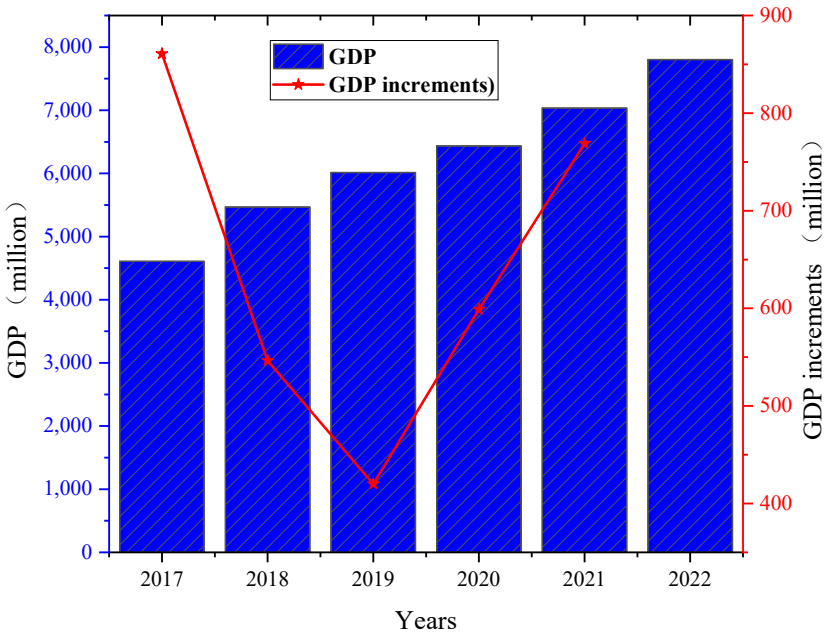

Figure 6 Total GDP and GDP growth rate of Xiamen from 2017 to 2022 (Unit: 10,000 CNY)

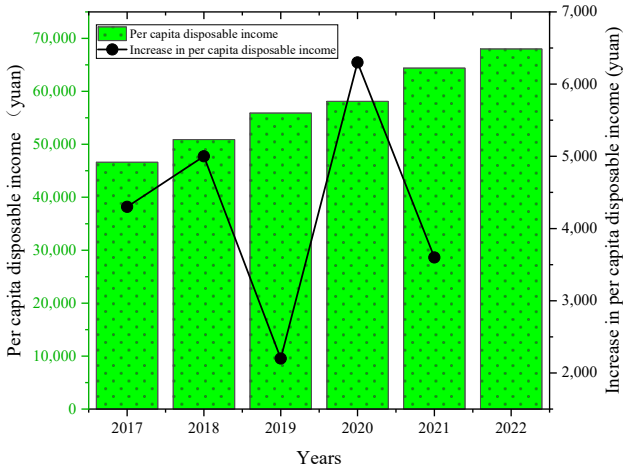

Figure 7 Total and incremental per capita disposable income in Xiamen from 2017 to 2022 (Unit: CNY)

Figures 6 and 7 illustrate an upward trajectory in Xiamen's economic landscape in recent years. Based on big data and correlation analysis, the future trend of music events in Xiamen can evolve towards diversification. By integrating regional characteristics and adhering to the concept of sustainable development, innovative themes and formats for music events can be introduced to promote progressive development.

3.2. Model experiment verification

To explore the relationship between users' music preferences and economic indicators across different regions, this work applies CNNs and RNNs to analyze music event and cultural tourism data collected from Xiamen between 2018 and 2022. The following section details the specific data analysis and experimental procedures: Initially, raw data undergoes rigorous cleaning and preprocessing to eliminate noise and outliers, ensuring the accuracy and reliability of the dataset. Subsequently, the CNN architecture is employed to extract spatial features from the music event and cultural tourism data, while the RNN structure captures temporal variations within these datasets. Detailed parameters used in the experimental setup are outlined in Table 4.

Table 4 Main parameters of the deep learning models

Model	Parameter	Value
CNN	Number of filters	32
	Filter size	3*3
	Activation function	ReLU
	Pooling layer	2*2
RNN	Unit type	LSTM
	Number of hidden units	128

The performance of the models is illustrated in Figure 8. The CNN and RNN combination achieves 91% accuracy on the training set, indicating a strong fit to the training data. On the validation and test sets, the model's performance slightly declines but maintaines an accuracy above 85%, showcasing robust generalization capability. The F1 score, akin to precision and recall, reflects balanced performance across both metrics.

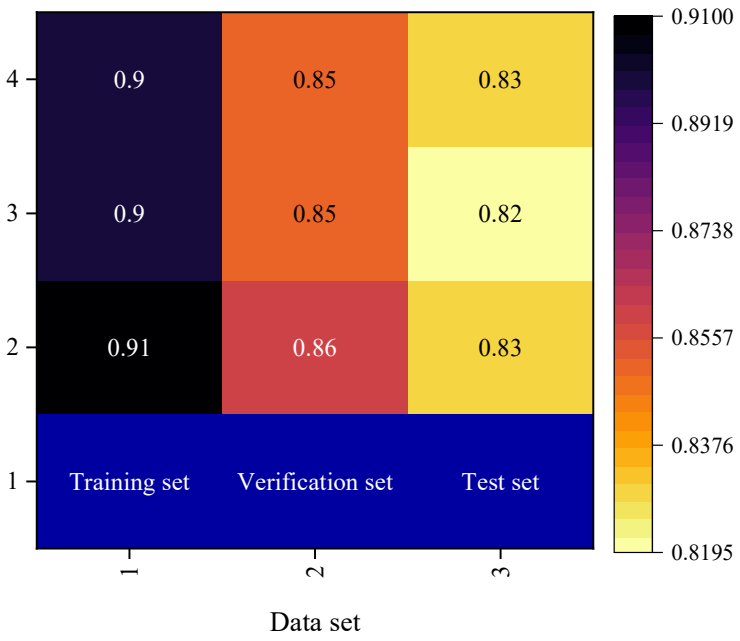

Figure 8 Performance of the model

Integrated feature representation involves merging spatial and temporal characteristics extracted from music events and cultural tourism data using DL models. These integrated features contribute significantly to the comprehensive representation of the correlation between user music preferences and regional economic indicators. Specifically, integrated features encompass the following aspects:

(1) Spatial Features: These features are extracted from music events and cultural tourism data using CNNs. They capture spatial variations in music preferences and cultural tourism characteristics across different regions.

(2) Temporal Features: Time-series data is processed using RNNs, revealing the dynamic relationship between music preferences and regional economies. CNN architecture facilitates the extraction of spatial features from music events and cultural tourism data. Through convolutional operations, the model automatically captures disparities in music preferences and cultural tourism features across diverse regions. RNN processes time-series data, capturing temporal fluctuations in music events and cultural tourism data. The outputs of CNN and RNN models are fused to obtain a more comprehensive feature representation. This approach enhances the model's ability to comprehend spatiotemporal relationships in music events and cultural tourism data.

(3) MLP: This model processes the integrated feature representation. With its multi-layer architecture, MLP identifies and models intricate nonlinear relationships between music preferences and regional economic indicators.

(4) DNN: DNN models augment the model's depth, thereby increasing sensitivity to potential correlations in the data. By stacking multiple hidden layers, DNN learns hierarchical abstract feature representations, comprehensively revealing the inherent connections between music preferences and regional economies.

MLP and DNN models undergo training and evaluation on integrated features to analyze predictive results, as depicted in Figure 9.

Figure 9 illustrates that the DNN model achieves lower mean absolute error (MAE) and mean squared error (MSE) in predictions compared to the MLP model, indicating superior performance of the DNN model in capturing the intricate relationships between music preferences and regional economic indicators. The higher correlation coefficient of the DNN model compared to the MLP model suggests that the DNN model offers more precise insights into the inherent connections between music preferences and regional economies. In summary, this work employs deep learning and big data analysis methods to extract integrated features from music events and cultural tourism data. MLP and DNN models are utilized for analysis, affirming the effectiveness of these models in predicting and uncovering complex relationships between music preferences and regional economic indicators.

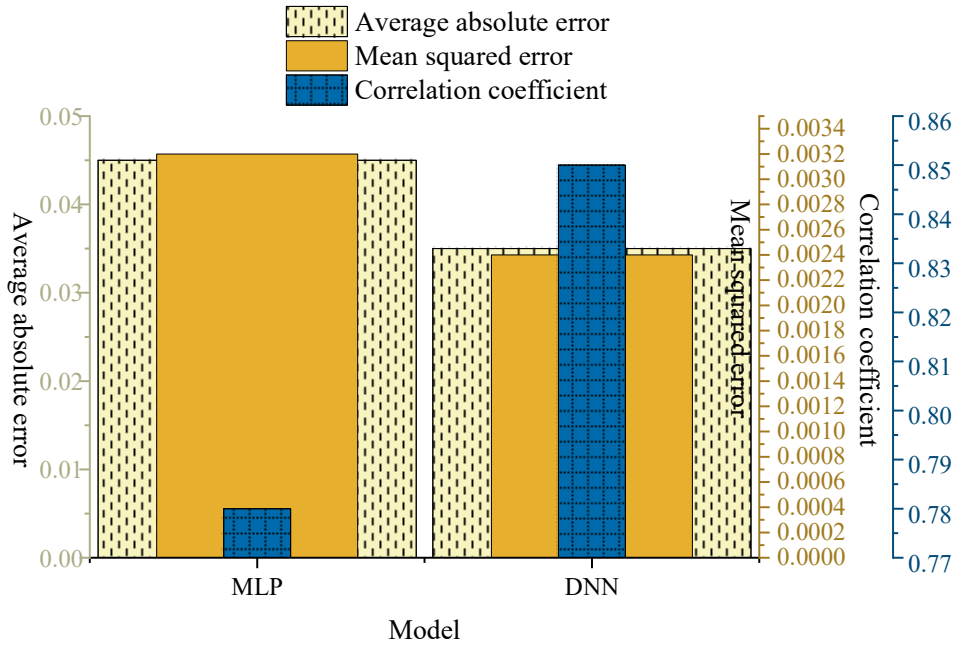

Figure 9 Model performance of MLP and DNN

3.3. Sustainable development of music events integrated with cultural tourism

Analyzing the regional attributes of Xiamen and employing innovative models that integrate music events with the cultural tourism sector based on sustainable development principles, the following development approaches are synthesized:

(1) Creating a journey of distinctive music

Amidst the global proliferation of music, Xiamen is encouraged to cultivate its unique music tourism intellectual property, utilizing insights from BDA to delineate distinct music preferences. This involves mapping out the trajectory of cultural tourism development and aligning the thematic focus of music events accordingly. It is essential to develop music event tourism itineraries that embody Xiamen's unique characteristics, while also exploring the social and market dynamics arising from the fusion of music events and tourism. Ensuring the vitality of both music events and the tourism industry is crucial. Moreover, operationalizing the concept of sustainable development is paramount, offering visitors a wholesome, trendy, and engaging music tourism experience. Ultimately, this initiative aims to foster a distinctive tourism sector centered around characteristic music, possibly leading to signature music events.

(2) Establishing a unique music event brand culture with strong correlation labels
In the Internet age, creating distinct and memorable cultural labels is essential for the longevity of cultural expressions. For Xiamen's music events, developing unique cultural identities is crucial to differentiate them amidst the global diversity of music genres and local specialties, aligned with the principles of characteristic music tourism. These labels should deeply resonate with the region's musical attributes, creating an immersive atmosphere in music events that allows tourists to gain profound insights, evoke enduring impressions, and forge lasting memories. Employing diverse strategies to consistently highlight these labels ensures that tourists perceive the rich regional cultural essence akin to renowned destinations such as the Old Town of Lijiang and Jiangnan Water Town.

(3) Music competitions and multicultural integration: complementary enrichment of artistic connotations
Music events in Xiamen, inherently intertwined with other art forms, should seamlessly integrate with natural and cultural landscapes to articulate diverse emotional nuances and artistic visions through distinctive mediums. This integration must uphold local ethos, appeal to tourists' aesthetic sensibilities, and amplify the unique artistic allure of Xiamen. Simultaneously, tourism activities should harmonize with the thematic essence of music events, showcasing Xiamen's distinctive regional and cultural attributes to provide visitors with a novel and immersive experience. They should fully harness music's role across the six travel elements of food, accommodation, transportation, tourism, shopping, and entertainment, thereby promoting regional culture, stimulating Xiamen's economic growth, and leveraging the strengths of its characteristic tourism industry chain.

(4) Innovating music event modes: clever utilization of big data platforms

Xiamen can leverage the core cultural essence of music events to enhance the appeal of tourism projects and products. This involves enriching tourism offerings with music-focused dimensions such as experiential, observational, health-oriented, and communicative aspects. Innovatively utilizing big data platforms can further elevate the popularity and discourse surrounding regional professional culture. Moreover, exploring innovative hosting modalities for music events—such as featuring distinguished guests to enhance participation and critique—can significantly boost event visibility, influence, and tourist allure. This approach not only serves as a form of publicity and expansion for the tourism industry but also enhances regional cultural outreach and tourism consumption levels. It fosters a mutually reinforcing trend of collaborative advancement between music events and the tourism sector, expanding artistic influence and enriching the overall cultural landscape.

4. Conclusion

This work's innovative contribution in predicting music preferences and analyzing regional economics lies in integrating DL and BDA technologies to conduct comprehensive analyses of music events and cultural tourism data in Xiamen. Initially, CNNs and RNNs are employed for feature engineering, extracting spatiotemporal characteristics from the data. This approach effectively demonstrates the correlations between music preferences and regional economies. Subsequently, correlation assessment methods are applied to analyze the relationships between user music preferences and regional GDP and per capita disposable income across different areas. Furthermore, MLP and DNN models are utilized to train large-scale datasets, optimize parameters, and simulate complex relationships between music choices and regional economic indicators. Through these DL models, this work conducts detailed correlation assessments, uncovering higher-order relationships within the data and providing profound insights for the sustainable development of music events and cultural tourism. The research findings indicate that DL-based methods accurately predict music preferences and elucidate the intricate interactions between music choices and regional economies. These insights offer novel perspectives and methodologies for building an innovative music tourism industry chain in Xiamen, thereby fostering sustainable local economic development. Additionally, this work reveals a negative correlation between music choice diversity and regional GDP and per capita disposable income. Conversely, diversity in user music preferences exhibits a positive correlation with both economic metrics, suggesting a mutually enhancing relationship between the diversity of music events and regional cultural tourism characteristics. These findings not only propose innovative development models for Xiamen's cultural tourism industry but also provide valuable experiences and insights for other regions seeking to develop tourism industry chains based on distinctive cultural assets within a big data framework. However, this work acknowledges several limitations. Primarily, due to constraints in data availability, the focus remains predominantly on the Xiamen area, limiting the broader applicability of the findings. Additionally, this work primarily investigates the correlation between music events and economic development, with insufficient consideration of other potential socio-cultural factors. Future research efforts could expand the scope of data collection to more deeply examine the impact of music events on local cultural heritage and social cohesion. Moreover, exploring methodologies aimed at preserving traditional culture amidst innovative transformations and sustainable development remains an area deserving further investigation.

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