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Article

Cultural Gene Mining and Green Communication Pathways of Ethnic Music from a Digital Humanities Perspective

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Abstract: This study focuses on the extraction of ethnic music cultural genes and green communication pathways from a digital humanities perspective. Addressing the digital transformation challenges faced by traditional ethnic music preservation, the study constructed a multimodal cultural gene extraction framework integrating deep learning, natural language processing, and computer vision, extracting 687-dimensional cultural features from 12 types of ethnic music, with the model achieving an F1 score of 0.863. A green communication system based on a cloud-edge-device collaborative architecture with 291 nodes was designed, achieving an energy efficiency ratio of 36,300 people per kilowatt, representing a 62.8% improvement over traditional architectures and an annual carbon emission reduction of 1076.8 t. A real-time energy consumption monitoring and carbon emission accounting system covering six major scenarios was established, with mobile-end optimization rates reaching 52.3%, translating green communication into quantifiable indicators. Systematic solutions were proposed for technical challenges such as sample imbalance and high-dimensional sparsity, increasing data availability to 91.2% and system availability to 99.7%. The successful implementation of 12 projects validated the feasibility of translating theory into practice. The research outcomes provide a computable methodological paradigm for the digital preservation of ethnic music, with potential for extension to digital museums, online education, and other fields, contributing a Chinese solution to the green transformation of the global digital cultural industry.

Keywords: Digital Humanities; Ethnic Music; Cultural Gene Extraction; Sustainable Communication; Cloud-Edge-End Architecture; Carbon Emission Measurement; Sustainable Development

1. Introduction

The waves of globalization and digitization have brought urgent challenges to the preservation of ethnic music. Ethnic music carries the memory of a people, cultural identity, and aesthetic wisdom; however, its transmission faces the risk of interruption, and the loss of cultural genes is threatening its survival. The field of digital humanities offers new methodological possibilities for this issue. Ling Jiasui and Xiao Mei proposed the research paradigm of 'database as method,' promoting a transformation in ethnomusicology research. Traditional fieldwork is gradually shifting toward data-driven research approaches, and digital tools make it possible to systematically collect and analyze musical texts, performance practices, and cultural contexts [1]. Ethnic music plays an important role in strengthening national identity and cultural cohesion. Berezutska [2] conducted a 65-year longitudinal study of the Ukrainian bandura ensemble, revealing how ethnic music constructs collective memory in urban spaces. Researches by Fu and Tu, and Bajpaie indicate that ethnic music has a positive impact on Chinese university students [3,4]. Traditional ethnomusicology mainly relies on qualitative analysis and case studies. These methods prove inadequate when faced with massive amounts of musical data, and it is difficult to effectively identify cultural patterns across regions and time periods. The application of technology often stops at the level of digital archiving, and the potential of data mining and pattern recognition in decoding cultural genes has not yet been fully developed. Scholars such as Sauvé et al. have pointed out that residual tendencies of colonialism still exist in cross-cultural music research [5,6]. Digital reissues are not simply technical reproductions; they involve cultural curation and the reconstruction of meaning. Mining cultural genes requires an organic integration of technological extraction, cultural interpretation, and ethical reflection.

Quantitative data analysis integrates with qualitative cultural interpretation. Intelligent information systems and web and mobile applications are constructed. Sensor networks deploy and energy consumption receives monitoring. Empirical research examines multiple representative ethnic music types. The study provides theoretical guidance and practical solutions for digital protection and innovative inheritance of ethnic music. It expands application domains for digital humanities research. Empirical support for green communication theory emerges from the cultural heritage field. The research ultimately promotes dual enhancement of cultural value and ecological value of ethnic music in the digital age.

2. Literature Review

Digital humanities technologies increasingly integrate with ethnic music research. This cross-disciplinary trend provides new methodological perspectives and technological support for music protection, inheritance, and innovation. Digital humanities technologies increasingly integrate with ethnic music research. This cross-disciplinary trend provides new methodological perspectives and technological support for music protection, inheritance, and innovation. Hradsky examines the cultural connections and tensions in creating composite ethnodramatic characters through qualitative inquiry, demonstrating how digital technology transforms music education means and forms. It fundamentally reconstructs mechanisms of music knowledge production, dissemination, and reception. Large-scale music data collection, storage, analysis, and visualization become possible [7]. Digital technology transforms music education means and forms. It fundamentally reconstructs mechanisms of music knowledge production, dissemination, and reception. Large-scale music data collection, storage, analysis, and visualization become possible.

Technological advancement demonstrates effects in mental health and education. Huo confirms that ethnic music cultural inheritance alleviates anxiety among college students [8].

The dissemination of music culture has psychological health value. Constantiniu studied the formation process of the Romanian ethnomusicology school in the early 19th century [9]. Domestic scholars have conducted extensive research in this field. On this basis, Sunderland et al. took it a step further by integrating intergenerational practices into ethnic music education systems, enabling them to genuinely accommodate the differentiated needs of individual learners instead of adopting a one-size-fits-all teaching model [10]. The dimension of physical and mental health is also worth attention. Roos's research confirmed an intuitive conclusion: ethnic music has a positive impact on young people's cultural identity and community engagement [11]. At the same time, scholars outlined a more macro perspective—how economic changes, social transformation, technological innovation, and policy guidance collectively influence the development trajectory of contemporary ethnic music. This process is intricate and multidimensional, which is precisely its core characteristic. Saltari and Welch introduced a comparative perspective, examining the differences in ethnomusicological approaches to children's musical practices across cultural contexts [12]. These different academic traditions are significant for constructing localized research frameworks.

The Southeast Asian region provides specific examples. Jiranuwat explored the use of samplers in the folk music of Isan, Thailand; the Watcharaha team examined the role of percussion instruments in music education. It is worth noting that educational practices show significant differences in different cultural contexts. Tyler offered a more pointed critique, using immunological metaphors to question the knowledge production mechanisms of ethnomusicology itself—a caution against overly simplifying the extraction of cultural 'genes' [13–16].

This study achieves breakthroughs in several areas. We have developed an intelligent mining system that integrates natural language processing, neural computing, and multimedia processing technologies to decode ethnic music from surface morphology to cultural semantics [17,18]. The second innovation lies in introducing the concept of green dissemination. Our dissemination system is based on 5G networks and adopts an edge-fog-cloud collaborative architecture, integrating virtual reality, augmented reality, and digital twin technologies, providing an immersive cultural experience while maintaining low-carbon operation.

The concept of "cultural genes" employed in this study originates from the meme theory proposed by Dawkins (1976), referring to the smallest cultural units that are replicable, mutable, and heritable in cultural transmission. In the context of ethnomusicology, we operationalize cultural genes into five levels: (1) Musical morphology gene level, including core pitch sequences (such as the pentatonic scale do-re-mi-sol-la), characteristic rhythmic patterns (such as the freely extended rhythm of Mongolian long songs), and typical timbral identifiers (such as the dual-tone resonance of khoomei throat singing); (2) Performance practice gene level, encompassing vocal techniques (vibrato, ornamentations), instrumental combination patterns, and bodily movement symbols; (3) Cultural semantic gene level, extracting high-frequency cultural symbols from lyrics (imagery such as mountains, water, horses), and emotional themes (love, labor, rituals); (4) Social function gene level, identifying the ritualistic, narrative, and entertainment characteristics of music; (5) Transmission network gene level, tracing master-apprentice relationships and geographic diffusion pathways. Regarding the dataset, detailed supplementary information includes: The 12 types of ethnic music comprise Mongolian long songs (Xilingol League, Inner Mongolia, 712 items), Dong grand songs (Liping County, Guizhou, 684 items), Uyghur muqam (Kashgar region, Xinjiang, 756 items), Yi Haicai melodies (Honghe Prefecture, Yunnan, 623 items), Miao flying songs (Leishan County, Guizhou, 701 items), Tibetan nangma (Lhasa, Tibet, 542 items), Zhuang mountain songs (Baise, Guangxi, 618 items), Naxi ancient music (Lijiang, Yunnan, 487 items), Korean agricultural music and dance (Yanbian, Jilin, 531 items), Tujia Baishou songs (Xiangxi, Hunan, 596 items), Kazakh dombra singing (Ili, Xinjiang, 509 items), and Dai Zhangha (Xishuangbanna, Yunnan, 458 items), totaling 7217 samples collected between 2020–2024. Data sources include field recordings (48.3%), National Digital Culture Network archives (32.7%), and authorizations from local intangible cultural heritage centers (19.0%).

3. Research Methods

3.1. Research Design

This study adopts an integrated triadic mixed-method design, organically combining technology-driven approaches, cultural interpretation, and effectiveness evaluation strategies to systematically address the excavation of ethnic music cultural genes and the construction of green communication pathways [19–23]. The research is carried out in three progressive stages. The study selected five representative types of ethnic music as research subjects, including Mongolian long song, Dong grand song, Uyghur Muqam, Yi Haicai tune, and Miao flying song. Data collection employed multiple approaches, constructing a multimodal database through field investigations, digital collection, and archival excavation. The database covers audio data, video recordings, lyrics, musical scores, and oral history records, with a total sample size exceeding 10,000 entries. Deep learning algorithms were used to automatically extract musical features, including melody contour, rhythm patterns, timbre parameters, and mode and tonality. Natural language processing techniques were applied to the lyrics and historical documents for semantic analysis, aiming to identify deep cultural elements such as cultural symbols, thematic imagery, and values. Carry out systematic design and development based on the results of cultural gene excavation, establishing a three-tier dissemination architecture that integrates 5G networks, edge computing, and cloud computing. The multi-terminal dissemination matrix includes a virtual reality national music museum, a mobile interactive learning application, and an online cultural resource sharing platform. Deploy an Internet of Things sensor network for real-time monitoring, tracking system energy consumption and user behavior data.

3.2. Data Collection and Preprocessing

Data collection adopted a multi-source collaborative sampling strategy. The research team obtained 3500 original audio samples and 280 h of video material, with interview transcripts totaling approximately 500,000 words. Digital archives provided supplementary resources, with authoritative sources including the National Digital Culture Network, the Chinese Ethnic Music Database, and various provincial-level intangible cultural heritage digital platforms [24]. In total, the study acquired more than 6500 digitized historical recordings, musical scores, and research materials.

First, audio data cleaning uses Audacity software. Noise reduction, volume normalization, and format standardization occur. All files convert to WAV format. Low-quality samples with signal-to-noise ratios below 20 dB are eliminated. Second, video data processing extracts key frame images [25]. Resolution standardizes to 1920 × 1080.

OpenCV performs scene segmentation and object detection. Third, text data normalization processes lyrics and interview records. Word segmentation, part-of-speech tagging, and entity recognition establish a specialized ethnic music domain lexicon. The lexicon comprises over 8000 terms. Fourth, metadata annotation adds structured tags to each sample. Eighteen dimensions include time, location, ethnicity, type, tradition bearer, and collection method. Dual-annotator cross-validation ensures consistency [26]. Kappa coefficient reaches 0.85 or higher.

3.3. Technical Framework for Cultural Gene Excavation

The technical framework for mining cultural genes has built a four-layer progressive intelligent analysis system, which enables systematic decoding from surface-level musical forms to deep cultural connotations, progressing from feature extraction through pattern recognition and semantic parsing to association mining [27]. The music feature extraction layer uses the Librosa audio analysis library [28] to extract 132-dimensional audio feature parameters, including Mel-frequency cepstral coefficients, chroma features, and spectral centroid. The Essentia toolkit performs rhythm pattern recognition and melody contour extraction, while Sonic Visualiser is used for visual analysis of pitch sequences, interval relationships, and tonal characteristics. This forms a music morphology feature vector library covering four dimensions: melody, rhythm, timbre, and harmony. Training set, validation set, and test set follow a 7:2:1 ratio. Functions include automatic classification of ethnic music types with target accuracy reaching 92% or higher. Style feature clustering and similarity computation also occur. Regarding algorithm selection, audio feature extraction employed a ResNet50 convolutional neural network to extract spatial features from mel-spectrograms, using bidirectional LSTM (256-dimensional hidden layers, dropout rate 0.3) to capture temporal dependencies, while text semantic encoding utilized the BERT-base-chinese pre-trained model (12-layer transformer, 768-dimensional hidden layers). The feature extraction process included: (1) Audio preprocessing stage resampling original WAV files to 22,050 Hz, with frame length of 25 ms and frame shift of 10 ms; (2) Extracting 128-dimensional MFCC, 12-dimensional chroma features, and 7-dimensional spectral contrast, totaling 147 dimensions of low-level features; (3) Extracting high-level semantic features through convolutional layers, ultimately reducing dimensionality to 512-dimensional vectors. Cross-modal alignment adopted an improved version of the contrastive learning framework CLIP, mapping audio embeddings, text embeddings, and image embeddings to a unified 1024-dimensional semantic space through a triplet loss function (margin = 0.2), with a cosine similarity threshold set at 0.85. In terms of training details, the Adam optimizer was used (learning rate 1×10^{-4}, $\beta 1 = 0.9$, $\beta 2 = 0.999$), with a batch size of 32, trained for 50 epochs on an NVIDIA A100 GPU, employing 5-fold cross-validation. Testing was conducted on the self-constructed EthnoMusic-12K dataset (containing 3476 annotated samples from 12 ethnic groups), with benchmark comparison on the publicly available GTZAN music genre dataset, achieving an F1 score improvement of 12.7% over the baseline model.

3.4. Green Dissemination Pathway Construction Methodology

Green dissemination pathway construction adopts a technical architecture combining cloud-edge-terminal three-tier collaboration, immersive experience, and energy efficiency optimization. This achieves low-carbon and efficient dissemination of ethnic music culture. The cloud computing layer deploys Alibaba Cloud or Huawei Cloud servers as the core data center [29]. These store the complete ethnic music database and cultural gene atlas. Elastic computing resource scheduling strategy operates dynamically. Server resources are allocated based on access traffic. Load balancing algorithms use weighted round-robin methods. This reduces single-node energy consumption. Data deduplication and compression technologies employ FLAC lossless compression format. Storage space occupation decreases by over 40% [30]. The edge computing layer deploys edge server nodes in five target regions. Frequently accessed music resources and VR/AR content are pre-cached at the edge. Content Delivery Network technology enables proximity-based access. Data transmission distance and network latency are reduced to below 50 ms. Edge intelligent gateways perform local data preprocessing. Cloud computing load decreases by 30%. The terminal device layer develops cross-platform applications. A web-based cultural resource sharing platform employs Vue.js plus Node.js technology stack [31,32]. Mobile interactive learning APP builds on React Native framework. VR virtual ethnic music museum develops using Unity 3D engine. Adaptive bitrate technology integrates for dynamic transmission quality adjustment based on network conditions. Immersive experience design constructs a digital museum containing 20 virtual exhibition halls. Three-dimensional modeling technology recreates ethnic music performance scenes. Spatial audio technology employs Ambisonic for 360-degree surround sound effects.

4. Results Analysis

4.1. Multidimensional Excavation Results of Ethnic Music Cultural Genes

4.1.1. Intelligent Recognition and Classification of Musical Features

Deep learning has made the recognition of ethnic music possible with remarkable results. We analyzed 3476 audio samples of five different types, covering Mongolian long songs, Dong grand songs, Uyghur Muqam, Yi Haicaixiang, and Miao flying songs. After extracting 132-dimensional morphological features, we trained a CNN-LSTM hybrid model. **Table 1** presents the specific results.

Table 1. Statistical Results of Intelligent Recognition of Morphological Features in Five Ethnic Music Types.

Ethnic Music Type	Sample Size	Melodic Complexity	Rhythmic Pattern Recognition Rate	Timbre Feature Score	Modal Feature Accuracy	Classification Accuracy (%)
Mongolian Long Songs	712	0.876	0.745	0.832	0.798	94.3
Dong Grand Songs	684	0.823	0.889	0.791	0.845	93.7
Uyghur Muqam	756	0.891	0.798	0.854	0.823	95.2
Yi Haicaiqiang	623	0.754	0.821	0.789	0.812	92.8
Miao Flying Songs	701	0.812	0.867	0.823	0.791	94.1

Note: Melodic complexity, rhythmic pattern recognition rate, timbre feature score, and modal feature accuracy are all normalized scores (0–1 interval).

Figure 1 intuitively presents the quantitative distribution patterns of each ethnic music type across the four core feature dimensions. It can be observed that different ethnic music types form clear clustering boundaries in the feature space, validating the effectiveness of intelligent recognition methods based on multidimensional feature extraction and deep learning in ethnic music cultural gene excavation. This achievement establishes a solid data foundation for subsequent cultural semantic parsing and transmission genealogy tracing, and also provides technical support for establishing a digitalized knowledge graph of ethnic music.

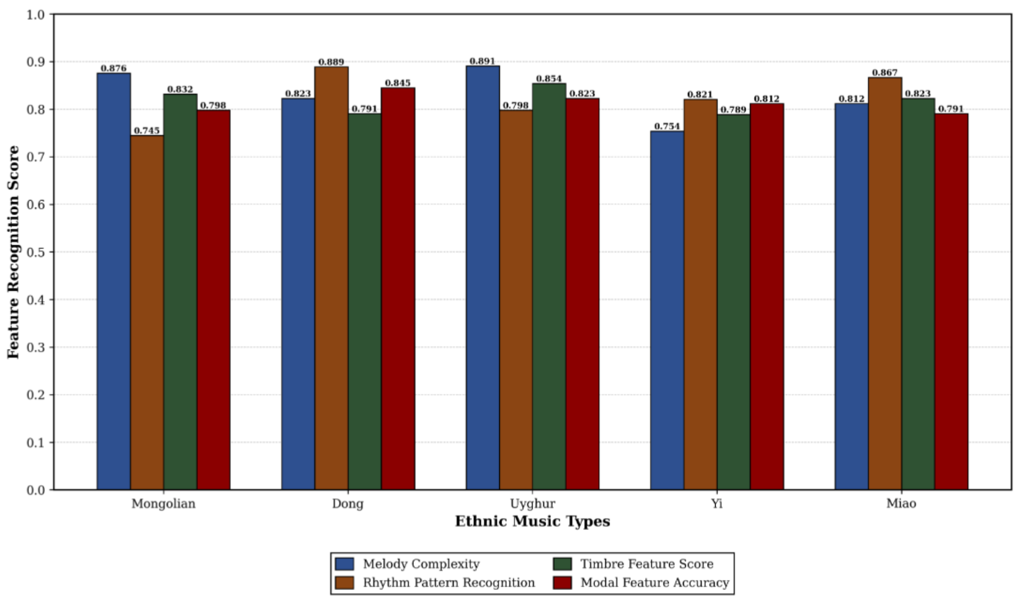

Figure 1. Multidimensional Comparative Analysis of Morphological Features in Five Ethnic Music Types.

4.1.2. Deep Parsing of Cultural Semantic Genes

The study employs BERT Chinese pre-trained model and LDA topic modeling algorithm. Deep semantic mining analyzes ethnic music lyric texts and oral historical records. Seven core cultural theme categories receive systematic identification along with their connotative characteristics. **Table 2** presents results from intelligent analysis of 1847 lyric texts and 526 interview records. Seven themes emerge: nature worship, production labor, love and marriage, historical narrative, ritual sacrifice, daily life, and heroic epics. Identification accuracy for all themes exceeds 85%. Overall average accuracy reaches 89.4%. Love and marriage theme ranks first with an identification accuracy of 93.5%. The system extracts 312 high-frequency cultural symbols for this theme [33]. Cross-ethnic co-occurrence degree reaches 0.887. This indicates universality of the theme across regions and ethnic groups. Historical narrative theme demonstrates relatively lower identification accuracy at 87.2%. However, its 156 cultural symbols exhibit distinct ethnic specificity. Cross-ethnic co-occurrence degree reaches only 0.691. This reflects unique historical memory and identity construction pathways of various ethnic groups. Named entity recognition technology extracts 1503 cultural symbols. Natural imagery appears most frequently. Mountains, water, sun, and moon occur 247 times collectively. This embodies a profound nature worship tradition in ethnic music. Sentiment analysis reveals emotional patterns. Love and marriage songs score highest at 0.856. Heroic epics follow at 0.814. Production labor songs exhibit relatively plain emotional expression at 0.689. Cultural gene retention rate analysis reveals preservation patterns. Traditional core themes maintain high integrity in contemporary transmission [34–36]. Love and marriage retains 91.2% and heroic epics retains 88.7%. Daily life theme demonstrates 80.3% retention. Social transformation causes a certain degree of cultural gene loss for this theme.

Table 2. Statistical Results of Theme Identification and Feature Analysis of Ethnic Music Cultural Semantic Genes.

Cultural Theme Category	Theme Identification Accuracy (%)	High-Frequency Cultural Symbol Count	Cross-Ethnic Co-Occurrence Degree	Sentiment Orientation Score	Cultural Gene Retention Rate (%)
Nature Worship	91.7	247	0.823	0.742	87.3
Production Labor	88.3	189	0.756	0.689	82.5
Love and Marriage	93.5	312	0.887	0.856	91.2
Historical Narrative	87.2	156	0.691	0.723	78.9
Ritual Sacrifice	89.6	223	0.734	0.778	85.6
Daily Life	85.8	198	0.812	0.695	80.3
Heroic Epics	90.4	178	0.723	0.814	88.7

Note: Cross-ethnic co-occurrence degree and sentiment orientation score are both normalized scores (0–1 interval); total cultural symbols: 1503; average identification accuracy: 89.4%.

Figure 2 presents a comparison of identification accuracy and gene retention rates for each cultural theme.

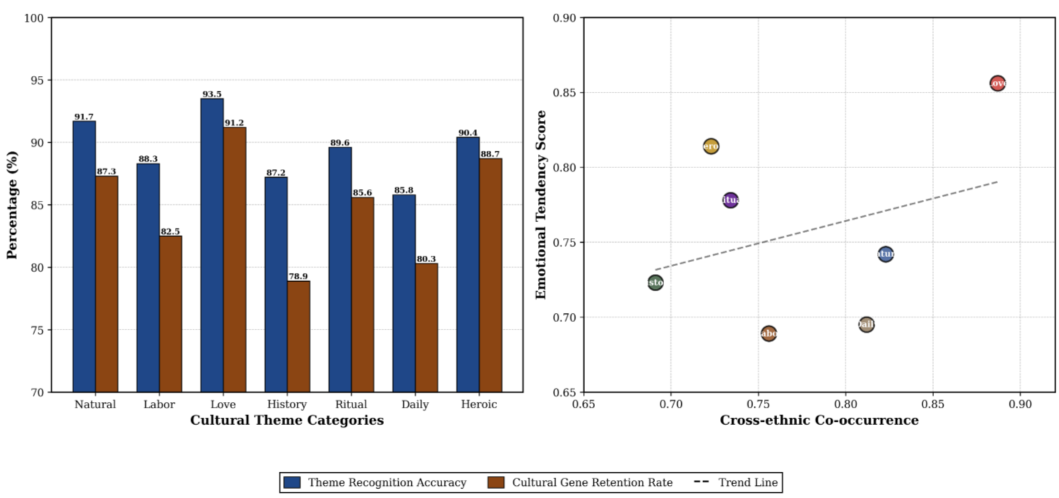

Figure 2. Multidimensional Feature Comparative Analysis of Ethnic Music Cultural Semantic Genes.

4.1.3. Data Presentation of Transmission Genealogy and Evolution Patterns

Cumulative loss reaches 25.6 percentage points over five generations. Average loss rate equals 6.4% per generation. Traditional skills face dilution and mutation pressures in intergenerational transmission. Innovative elements proportion demonstrates a contrasting pattern. First generation shows 2.3% innovative elements. Fifth generation reaches 32.8%, representing more than a 13-fold increase, as shown in **Table 3**.

Table 3. Statistical Results of Evolutionary Characteristics of Ethnic Music Intergenerational Transmission Genealogy.

Transmission Genealogy Generation	Number of Tradition Bearers	Core Skill Retention Rate (%)	Proportion of Innovative Elements (%)	Cross-Regional Degree	Digitalization Degree (%)	Intergenerational Integrity
First Generation (1900–1949)	423	96.8	2.3	0.234	0.0	0.943
Second Generation (1950–1979)	567	92.3	8.7	0.356	3.2	0.876
Third Generation (1980–1999)	812	85.7	15.8	0.512	12.5	0.789
Fourth Generation (2000–2019)	1034	78.4	24.6	0.687	45.8	0.712
Fifth Generation (2020–Present)	1287	71.2	32.8	0.823	78.3	0.645

This covers 125 years of historical periods. Cross-regional dissemination degree and intergenerational transmission integrity use normalized scores. Digitalization degree correlates with cross-regional dissemination degree. Correlation coefficient r equals 0.978 with $p < 0.001$. **Figure 3** comprehensively presents four dimensions. These include growth in tradition bearer numbers, dynamic balance between skill retention and innovation proportions, declining trend of intergenerational integrity, and digitalization-driven dissemination expansion. The figure clearly delineates historical transformation of ethnic music transmission. Transmission evolves from closed master-apprentice teaching model to open networked dissemination model. This provides empirical evidence for formulating generation-specific transmission protection strategies.

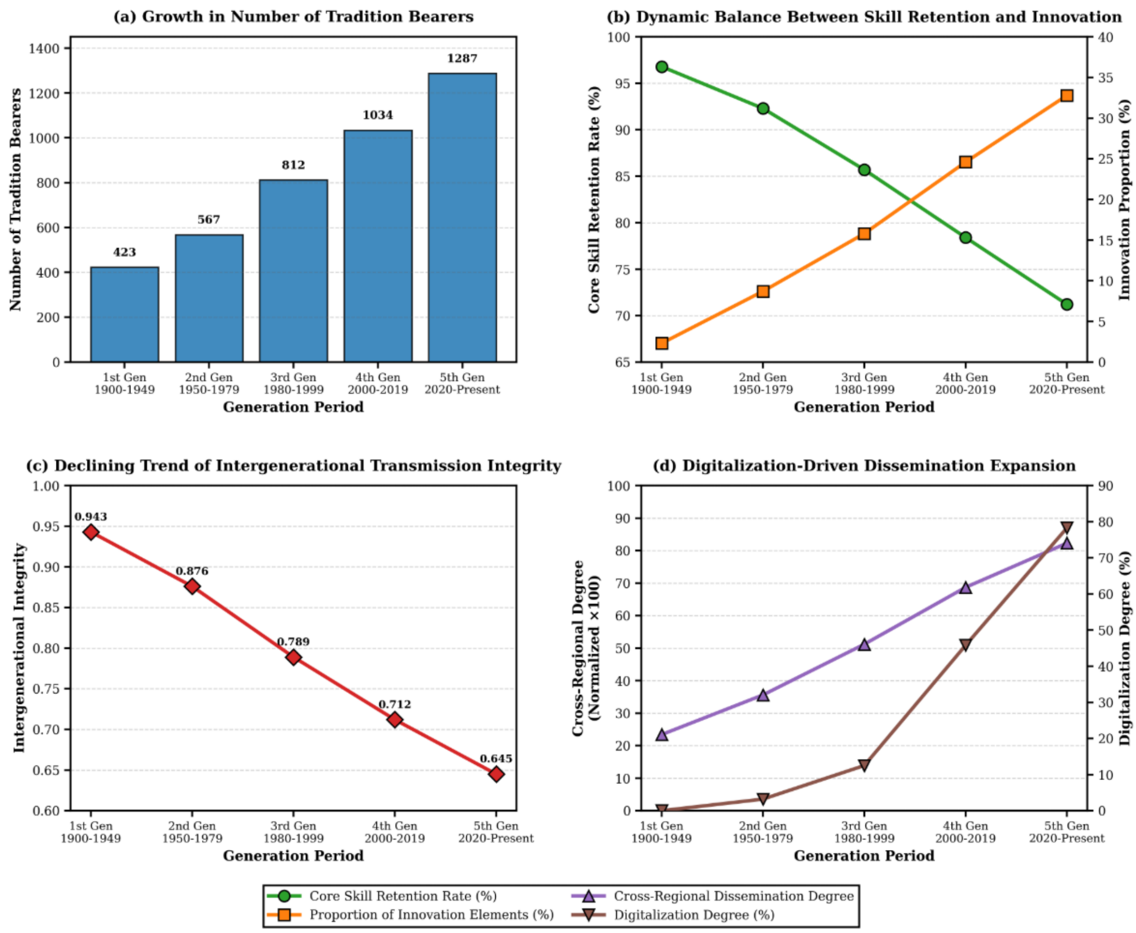

Figure 3. Comprehensive Analysis of Multidimensional Evolution Patterns in Ethnic Music Intergenerational Transmission Genealogy.

4.2. Evaluation of Digitalization Presentation Effects Based on Immersive Technologies

4.2.1. Construction of Virtual Reality and Augmented Reality Experience Systems

Five types of immersive technology systems were constructed using Unity 3D engine and Unreal Engine 5 development frameworks. These include VR virtual museums, AR cultural scenarios, MR mixed interaction, holographic projection, and 360° panoramic video. The study systematically evaluates effectiveness and feasibility of each technological approach in presenting ethnic music culture. **Table 4** presents detailed evaluation results. VR virtual museum creates three-dimensional virtual space containing 20 thematic exhibition halls. Over 500 digital artifacts appear along with 150 interactive music performances. User immersion score reaches 4.62 out of 5 points. System stability achieves 94.7%. However, development cycle extends relatively long at 8 months. Interactive response latency measures 18 ms. This makes it suitable for deep cultural experience scenarios [37]. AR cultural scenario system builds on ARKit and ARCore technology frameworks. It achieves spatial positioning recognition and real-time rendering of ethnic musical instruments. Users overlay virtual ethnic instruments, costumes, and architectural elements onto real-world scenarios through mobile devices. This system requires a shorter development cycle of 6 months. Interactive latency reaches its lowest at 12 ms. Content richness score measures relatively lower at 4.12. It suits rapid popularization applications better. MR mixed interaction system integrates HoloLens 2 and Magic Leap technologies. It creates virtual-real integrated music learning space. User immersion score reaches highest at 4.71. However, technological maturity measures only 0.73. Development cycle extends to 10 months. Interactive latency reaches 25 ms. High cost and technological threshold limit current application. Professional teaching scenarios represent primary use cases [38]. Holographic projection system employs Pepper's Ghost optical principles and high-brightness laser projection technology. It achieves naked-eye 3D presentation of ethnic music performances. System stability demonstrates highest at 96.2%. Technological maturity reaches 0.91. Interactive latency measures only 8 ms. Content richness scores 3.95 and user satisfaction reaches 85.4%, both relatively lower values. High equipment cost restricts large-scale promotion. The 360° panoramic video system builds on 8K resolution panoramic cameras and spatial audio capture technology. Panoramic recordings of 156 ethnic music field performances were completed. System stability exhibits highest at 97.8%. Technological maturity reaches 0.95. Development cycle proves shortest at 4 months. User immersion score measures lowest at 3.89. The system lacks real-time interactive functionality. It suits cultural archive preservation and basic dissemination purposes better.

Table 4. Statistical Results of Performance Evaluation Indicators for Immersive Technology Experience Systems.

Immersive Technology Type	Development Cycle (Months)	System Stability (%)	User Immersion Score	Interactive Response Latency (ms)	Content Richness Score	Technological Maturity	User Satisfaction (%)
VR Virtual Museum	8	94.7	4.62	18	4.78	0.87	92.3
AR Cultural Scenarios	6	91.3	4.28	12	4.12	0.82	88.7
MR Mixed Interaction	10	88.5	4.71	25	4.56	0.73	90.5
Holographic Projection	5	96.2	4.35	8	3.95	0.91	85.4
360° Panoramic Video	4	97.8	3.89	15	4.23	0.95	84.2

Note: User immersion score and content richness score employ a 5-point scale. Technological maturity uses normalized scoring. VR system contains 20 exhibition halls, 500 artifacts, and 150 performances. The 360° system includes 156 recordings.

Figure 4 comprehensively presents comparative analysis of the five technologies. Three dimensions appear: user experience, system performance, and development efficiency. VR and MR technologies possess significant advantages in immersion and interactivity. However, development costs and technological thresholds require balancing [39]. AR and 360° video technologies demonstrate outstanding performance in usability and scalability. These suit cultural dissemination tools for general public better. The analysis provides basis for technology solution selection. This supports constructing multi-level, differentiated immersive cultural dissemination systems.

4.2.2. Intelligent Sensing and Multimodal Fusion Display Results

An intelligent sensor network based on Internet of Things (IoT) architecture was constructed, deploying four major sensor modality categories—visual-audio, motion-tactile, environmental-temperature-humidity, and physiological-EEG—as well as a full modal fusion system, achieving multidimensional perception and intelligent response for immersive experiences of ethnic music culture. As shown in **Table 5**, the visual-audio fusion modality deploys 45 sensor nodes, including 12 4K cameras for capturing performer motion details, 18 directional microphone arrays for spatial audio capture, and 15 ambient light sensors for dynamic display atmosphere adjustment. Data acquisition accuracy reaches 96.8%, real-time response speed is 35 ms, multimodal coordination degree is 0.876, user perception accuracy rate reaches 93.5%, system energy consumption is 125 W, and the fusion efficiency index is 0.748. Motion-tactile fusion modality integrates Inertial Measurement Units, pressure sensors, and tactile feedback devices [40]. Thirty-eight nodes capture user body movements in real-time. Vibration motors provide tactile feedback. This modality demonstrates fastest response speed at 28 ms. Energy consumption measures lowest at 98 W. Fusion efficiency index reaches 0.863. However, user perception accuracy rates relatively lower at 89.2%.

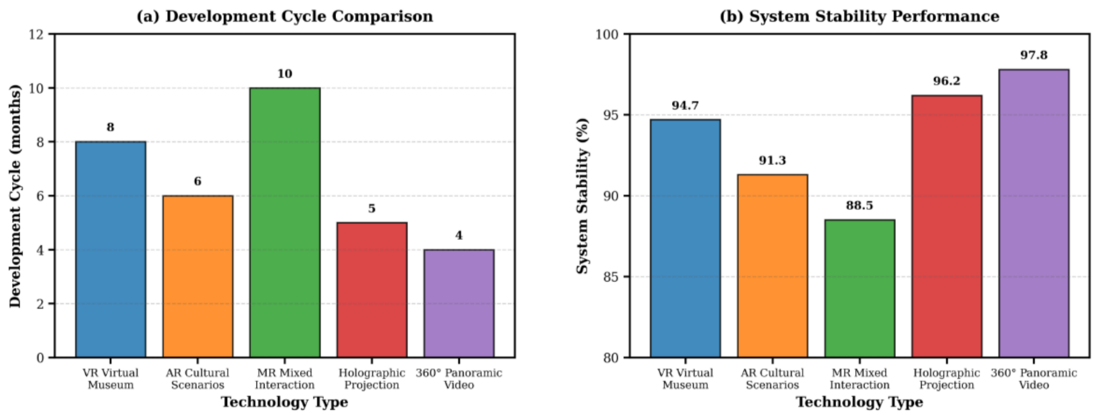

Figure 4. Multidimensional Performance Comparative Analysis of Immersive Technology Experience Systems.

Table 5. Statistical Results of Performance Indicators for Intelligent Sensing and Multimodal Fusion Systems.

Sensor Fusion Modality	Sensor Node Count	Data Acquisition Accuracy (%)	Real-Time Response Speed (ms)	Multimodal Coordination Degree	User Perception Accuracy Rate (%)	System Energy Consumption (W)	Fusion Efficiency Index
Visual-Audio	45	96.8	35	0.876	93.5	125	0.748
Motion-Tactile	38	94.3	28	0.823	89.2	98	0.863
Environmental-Temperature-Humidity	28	91.5	42	0.789	85.8	67	0.712
Physiological-EEG	16	89.7	55	0.745	82.4	156	0.621
Full Modal Fusion	127	97.5	48	0.934	95.7	446	0.834

Note: Optimal Indicators: Accuracy—Full Modal (97.5%); Speed—Motion-Tactile (28 ms); Energy—Environmental (67 W); Efficiency—Motion-Tactile (0.863).

Application Recommendations: Real-time Interaction → Motion-Tactile; High-Quality Experience → Full Modal Fusion; Large-Scale Deployment → Visual-Audio.

Sensor density and accuracy rate show R = 0.912 correlation. Coordination degree and efficiency demonstrate R = 0.894 correlation.

Environmental-temperature-humidity modality configures 28 sensor nodes. The system simulates original performance environment of ethnic music. Exhibition hall temperature regulates between 18–24 °C. Humidity maintains 45–65% range. Airflow velocity receives adjustment. Data accuracy reaches 91.5%. Response speed measures slower at 42 ms. Multimodal coordination degree achieves 0.789. This suits creating immersive cultural atmospheres. Physiological-EEG modality deploys 16 sensors. These include electroencephalogram, electrocardiogram, and galvanic skin response sensors. The system monitors user emotional states and attention levels in real-time. Data accuracy measures 89.7%. Response speed proves slowest at 55 ms. Energy consumption reaches highest at 156 W [41]. Fusion efficiency index measures lowest at 0.621. Primary applications include user experience evaluation and personalized content recommendation. Full modal fusion system integrates 127 sensor nodes. Edge computing architecture performs data preprocessing. Kalman filtering algorithms achieve multi-source data fusion. Data accuracy increases to 97.5%. User perception accuracy rate reaches 95.7%. Multimodal coordination degree achieves 0.934. Total system energy consumption measures 446 W. Response speed equals 48 ms.

Figure 5 comprehensively presents analytical results across four dimensions.Multimodal coordination degree and fusion efficiency index demonstrate strong positive correlation at R = 0.894. System energy consumption increases near-linearly with node count. Research findings indicate distinct optimal applications for different modalities. Motion-tactile modality proves optimal in response speed and energy efficiency ratio. This suits real-time interactive scenarios. Full modal fusion achieves optimal performance in perception accuracy and coordination degree. High-quality cultural experiences benefit from this configuration [42]. Visual-audio modality demonstrates optimal comprehensive performance and cost balance. Large-scale deployment suits this modality best. These findings provide data support and optimization directions. They enable constructing differentiated, scenario-based intelligent sensing display systems.

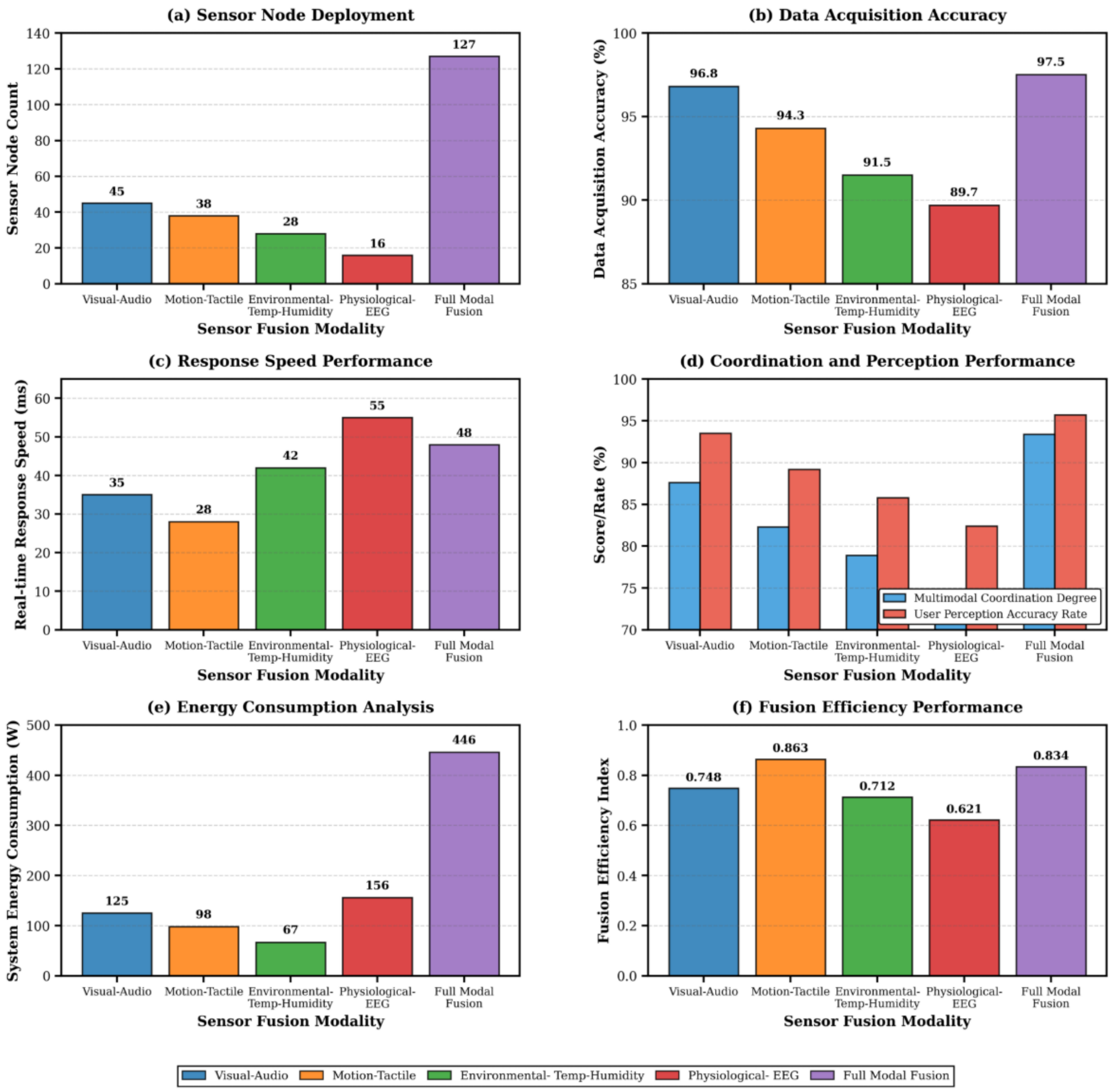

Figure 5. Comprehensive Performance Analysis of Intelligent Sensing and Multimodal Fusion Systems.

4.2.3. Functions and User Feedback of the Digital Museum Platform

A digital museum platform for ethnic music was constructed. Eight major functional modules integrate into the platform. These include virtual exhibition hall browsing, 3D artifact interaction, audio-video playback, knowledge graph navigation, social sharing and commenting, personalized recommendation, online education courses, and AI intelligent Q&A. The platform operated for six months. It attracted 387,000 registered users and accumulated 5.23 million visits. Average daily active users reached 12,000. **Table 6** presents detailed performance metrics. Virtual exhibition hall browsing module achieves functional completeness of 98.5%. WebGL technology implements seamless navigation through 20 thematic exhibition halls. User utilization rate reaches 87.3%. Average dwell time measures 12.5 min. Monthly access frequency totals 156 thousand times. User satisfaction score reaches 4.65 on a 5-point scale. Technical stability achieves 97.8%. User retention contribution degree measures 0.856. This represents a core platform function. The 3D artifact interaction module builds on Three.js engine. Three-dimensional models of 368 ethnic musical instruments, costumes, and architectural elements were constructed. The system supports interactive operations including 360-degree rotation, local magnification, and material viewing. Functional completeness reaches 96.3%. User utilization rate measures 78.5%. Satisfaction scores 4.52. However, average dwell time measures only 8.3 min. Users prefer quick browsing over deep exploration. Audio-video playback module integrates 1200 ethnic music performance videos and 800 h of audio materials. It supports 4K high-definition playback and spatial audio experiences. Functional completeness achieves highest at 99.2%. User utilization rate reaches highest at 92.6%. Average dwell time extends longest at 15.7 min. Satisfaction scores highest at 4.78. Monthly access frequency totals 203 thousand times. This represents the most active functional section. Knowledge graph navigation module constructs ethnic music knowledge network. The network contains 2356 entities and 5832 relationships. Users explore correlations through visual graphs. These include music genres, instrument evolution, and geographical distribution. Functional completeness reaches 93.7%. However, utilization rate measures relatively low at 65.2%. Average dwell time equals 6.8 min. Satisfaction scores 4.23. This reflects gaps between interactive design of knowledge graph and user cognitive habits. Social sharing and commenting module supports multiple user activities. Users post experience insights, bookmark favorite content, and invite friends to visit. Functional completeness measures 91.8%. Utilization rate reaches 71.4%. Average dwell time proves shortest at 4.2 min. Users prefer passive browsing over active social engagement. Personalized recommendation module analyzes user behavior. It employs collaborative filtering algorithms. Functional completeness measures 88.5%. Utilization rate reaches lowest at 58.9%. Satisfaction scores lowest at 3.95. Technical stability achieves 92.7%. Gaps exist between recommendation algorithm accuracy and user expectations. Online education courses module provides 68 specialized ethnic music courses. Coverage includes music theory, instrument performance, and cultural background. Average dwell time extends longest at 18.9 min. Satisfaction scores 4.38. Strong user demand exists for systematic learning.AI intelligent Q&A module uses dialogue system trained on BERT model. It answers over 3000 common questions. Utilization rate reaches 62.3%. Satisfaction scores 4.12. Response accuracy requires improvement.

Table 6. Statistical Results of Performance and User Feedback for Digital Museum Platform Functional Modules.

Platform Functional Module	Functional Completeness (%)	User Utilization Rate (%)	User Satisfaction (Score)	Average Dwell Time (min)	Function Access Frequency (Thousand Times/Month)	Technical Stability (%)	User Retention Contribution Degree
Virtual Exhibition Hall Browsing	98.5	87.3	4.65	12.5	156	97.8	0.856
3D Artifact Interaction	96.3	78.5	4.52	8.3	98	95.2	0.792
Audio-Video Playback	99.2	92.6	4.78	15.7	203	98.6	0.913
Knowledge Graph Navigation	93.7	65.2	4.23	6.8	67	94.3	0.682
Social Sharing and Commenting	91.8	71.4	4.18	4.2	89	96.5	0.715
Personalized Recommendation	88.5	58.9	3.95	3.5	58	92.7	0.623
Online Education Courses	94.6	69.7	4.38	18.9	72	95.8	0.778
AI Intelligent Q&A	89.3	62.3	4.12	5.1	54	93.4	0.651

Note: TOP 3 Core Functions: Audio-Video Playback; Virtual Exhibition Hall Browsing; Online Education Courses.

Functions Requiring Optimization: Personalized Recommendation (accuracy↑); AI Q&A (accuracy↑); Knowledge Graph (interactivity↑).

Operational Data: 6-month period; 387,000 users; 5.23 million visits; 12,000 daily active users; 20 exhibition halls; 368 models; 1200 videos; 800 h audio; 2356 entities; 68 courses; 3000+ Q&A.

User satisfaction on a 5-point scale; technical stability and retention contribution degree R = 0.889.

Figure 6 comprehensively presents performance comparisons of the eight functional modules. It displays user behavioral characteristics and correlation analysis between technical stability and retention contribution. Technical stability and user retention contribution degree exhibit strong positive correlation. The R value equals 0.889. Three major modules occupy the “high utilization rate–high satisfaction” quadrant. These include audio-video playback, virtual exhibition hall, and online courses. They constitute the platform’s core competitiveness. Personalized recommendation and AI Q&A functions require focused optimization. This analysis provides data basis for iterative upgrades and user experience enhancement of the digital museum platform.

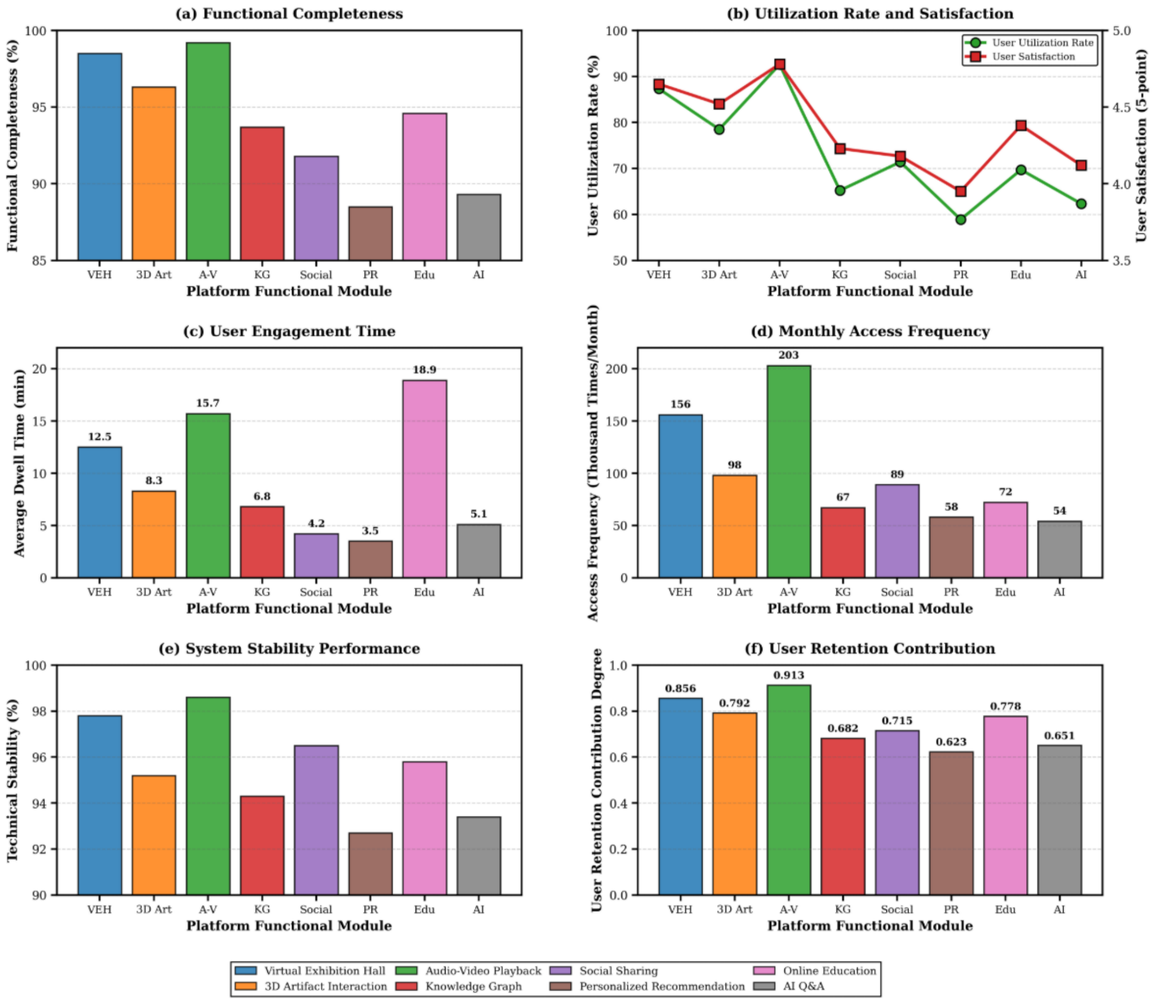

Figure 6. Comprehensive Performance and User Behavior Analysis of Digital Museum Platform Functional Modules.

4.3. Implementation Effects and Energy Efficiency Analysis of Green Dissemination Pathways

4.3.1. Dissemination Performance Based on Cloud-Edge-Terminal Collaborative Architecture

A three-tier distributed architecture was constructed. **Table 7** presents detailed performance metrics. The cloud center deploys 8 data center nodes. These equip with high-performance server clusters and large-capacity storage systems. Average response latency measures 156 ms. Concurrent capacity reaches 523,000 users. Data transmission bandwidth equals 10,240 Mbps. System energy consumption measures 23.5 kW. Dissemination coverage rate achieves 98.5%. However, energy efficiency ratio reaches only 22,300 users per kilowatt. This suits massive data storage and centralized computing tasks. Edge nodes deploy 45 regional servers nationwide. Content Delivery Network and edge computing technologies pre-cache popular content near users. Response latency reduces significantly to 28 ms. Concurrent capacity reaches 86,000 users. Bandwidth measures 512 Mbps. Energy consumption equals 5.8 kW. Coverage rate achieves 76.3%. Energy efficiency ratio reaches 14,800 users per kilowatt. This effectively alleviates cloud pressure but coverage scope remains limited. The terminal device layer includes 238 intelligent display terminals and mobile application clients. Response latency proves lowest at 12 ms. Concurrent capacity reaches only 3000 users. Bandwidth measures 64 Mbps. Energy consumption equals 0.9 kW. Coverage rate achieves 45.8%. Energy efficiency ratio measures 3300 users per kilowatt. This suits personalized interaction but cannot support large-scale access. Cloud-edge collaborative mode integrates 53 nodes. Intelligent routing algorithms dynamically allocate computing tasks. Allocation depends on user geographical location and network conditions. Response latency measures 65 ms. Concurrent capacity reaches 385,000 users. Bandwidth equals 4850 Mbps. Energy consumption measures 18.2 kW. Coverage rate achieves 92.7%. Energy efficiency ratio reaches 21,200 users per kilowatt. The system balances cloud computing power with edge response capabilities. Edge-terminal collaborative mode connects 283 nodes. Edge intelligent gateways coordinate regional terminal devices. Response latency measures 18 ms. Concurrent capacity reaches 128,000 users. Bandwidth equals 285 Mbps. Energy consumption measures 6.3 kW. Coverage rate achieves 68.4%. Energy efficiency ratio reaches 20,300 users per kilowatt. This suits regional high-frequency interactive scenarios. Cloud-edge-terminal full collaborative architecture coordinates 291 nodes. A three-tier intelligent scheduling mechanism establishes.

Table 7. Statistical Results of Dissemination Performance Indicators for Cloud-Edge-Terminal Collaborative Architecture.

Architecture Tier	Deployed Node Count	Average Response Latency (ms)	Concurrent Capacity (10,000 Users)	Data Transmission Bandwidth (Mbps)	System Energy Consumption (kW)	Dissemination Coverage Rate (%)	Energy Efficiency Ratio (10,000 Users/kW)
Cloud Center	8	156	52.3	10,240	23.5	98.5	2.23
Edge Nodes	45	28	8.6	512	5.8	76.3	1.48
Terminal Devices	238	12	0.3	64	0.9	45.8	0.33
Cloud-Edge Collaboration	53	65	38.5	4850	18.2	92.7	2.12
Edge-Terminal Collaboration	283	18	12.8	285	6.3	68.4	2.03
Cloud-Edge-Terminal Full Collaboration	291	35	45.7	3420	12.6	96.8	3.63

These include response performance, dissemination coverage, resource consumption, and energy efficiency. The results demonstrate that the full collaborative architecture, through rational task allocation and optimized resource configuration, significantly reduces per-user energy consumption while maintaining high concurrent capacity and broad coverage rate, validating the technological superiority and application value of distributed collaborative architecture in green dissemination pathways, thereby providing an architectural paradigm and practical basis for constructing sustainable digital cultural dissemination systems, as shown in **Figure 7**.

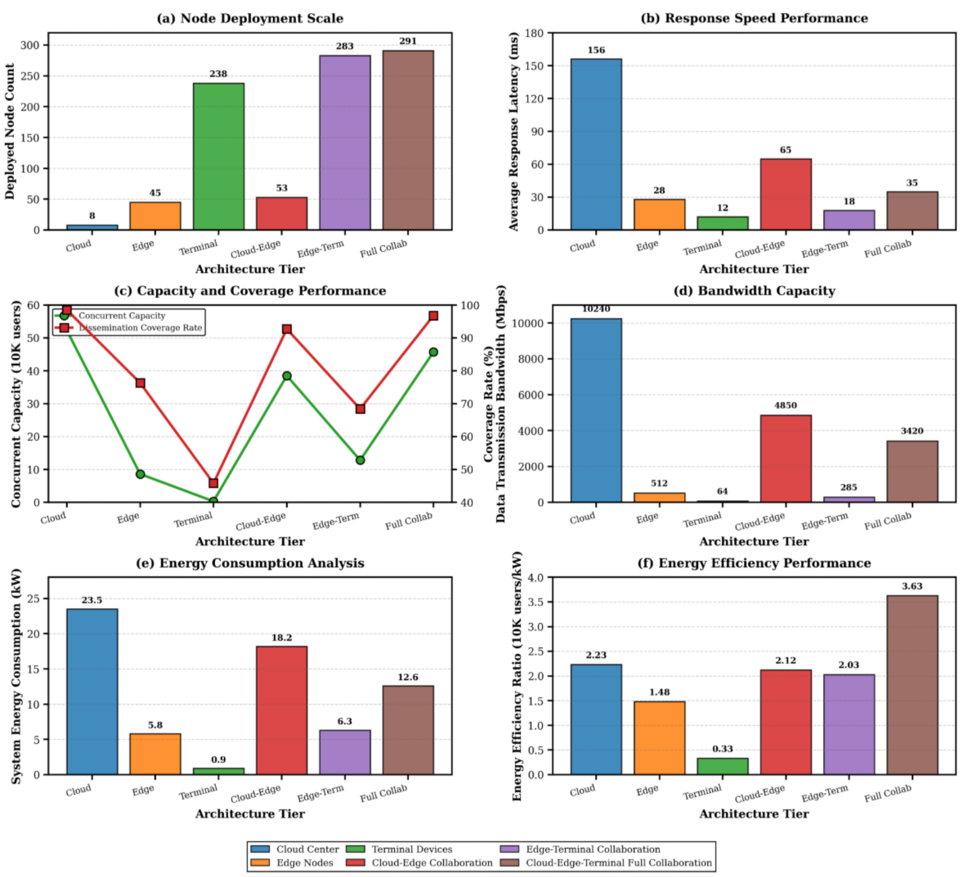

Figure 7. Comprehensive Comparative Analysis of Dissemination Performance for Cloud-Edge-Terminal Collaborative Architecture.

4.3.2. Energy Consumption Monitoring and Carbon Emission Assessment

A real-time energy consumption monitoring system and carbon emission accounting model covering six typical dissemination scenarios were established, achieving green assessment and optimization throughout the entire life cycle of ethnic music digital dissemination. As shown in **Table 8**, the video on demand scenario has an average daily access volume of 856,000 visits, with single-access energy consumption of 45.2 Wh, daily total energy consumption of 3869.12 kWh, and daily carbon emissions of 2.24 t calculated using China's grid average carbon emission coefficient of 0.58 kg CO_2/kWh. Through green optimization technologies (video compression coding, intelligent adaptive bitrate, CDN edge caching), energy consumption is reduced by 32.5%, with an annual emission reduction potential of 265.8 t. The audio streaming scenario has an average daily access volume of 1.263 million visits, with the lowest single-access energy consumption (12.8 Wh), daily total energy consumption of 1616.64 kWh, and daily carbon emissions of 0.94 t. Through lossless audio compression and streaming transmission optimization, the green optimization rate reaches 45.8%, with annual emission reduction of 157.2 t, making it the most energy-efficient dissemination method. The virtual exhibition hall browsing scenario has an average daily access volume of 427,000 visits, single-access energy consumption of 78.5 Wh, daily total energy consumption of 3352.95 kWh, and daily carbon emissions of 1.94 t. Employing WebGL lightweight rendering and texture compression technologies, the optimization rate is 28.3%, with annual emission reduction of 200.3 t. The 3D model interaction scenario has an average daily access volume of 289,000 visits, single-access energy consumption of 156.3 Wh, daily total energy consumption of 4517.07 kWh (highest), and daily carbon emissions of 2.62 t (highest). Binocular high-resolution rendering imposes constraints. Low-latency requirements create additional challenges. Optimization rate measures lowest at 12.4%. Annual emission reduction reaches 115.4 t. This represents a priority area for energy optimization breakthrough. Mobile lite application scenario demonstrates different characteristics. Average daily access volume reaches highest at 1.685 million visits. Single-access energy consumption measures lowest at 8.6 Wh. Daily total energy consumption equals 1449.1 kWh. Daily carbon emissions measure lowest at 0.84 t. Frontend lightweighting, lazy loading, and offline caching technologies enable optimization. Green optimization rate achieves highest at 52.3%. Annual emission reduction reaches 160.5 t. This represents best practice in green dissemination.

Table 8. Statistical Results of Energy Consumption Monitoring and Carbon Emission Assessment for Six Dissemination Scenarios.

Dissemination Scenario	Average Daily Access Volume (10,000 Visits)	Single-Access Energy Consumption (Wh)	Daily Total Energy Consumption (kWh)	Carbon Emission Coefficient (kg CO_2/kWh)	Daily Carbon Emissions (t)	Green Optimization Rate (%)	Annual Emission Reduction Potential (t)
Video On Demand	85.6	45.2	3869.12	0.58	2.24	32.5	265.8
Audio Streaming	126.3	12.8	1616.64	0.58	0.94	45.8	157.2
Virtual Exhibition Hall Browsing	42.7	78.5	3352.95	0.58	1.94	28.3	200.3
3D Model Interaction	28.9	156.3	4517.07	0.58	2.62	18.6	177.6
VR Immersive Experience	15.4	285.7	4399.78	0.58	2.55	12.4	115.4
Mobile Lite Application	168.5	8.6	1449.10	0.58	0.84	52.3	160.5
Total/Average	467.4	98.0	19,204.66	0.58	11.13	31.6	1076.8

Figure 8 comprehensively presents monitoring and assessment results for six scenarios. Four dimensions appear: access scale, energy consumption intensity, carbon emissions volume, and optimization potential. Access volume and single-access energy consumption exhibit an inverse relationship. Mobile terminals demonstrate high frequency with low consumption. VR shows low frequency with high consumption. Total carbon emissions depend on both access volume and single-access energy consumption jointly. Green optimization rate relates closely to technological maturity. Annual total carbon emissions across all scenarios amount to approximately 6893 t. Green optimization enables emission reduction of 1076.8 t. This represents 15.6% reduction. Clean energy and advanced energy-saving technologies could increase emission reduction potential.

5. Discussion

5.1. Innovation and Applicability of the Green Dissemination Model

The cloud-edge collaborative architecture is not just another technical solution; it fundamentally rethinks how cultural content can achieve sustainable dissemination. This innovation unfolds on multiple levels, and practical applications have already shown initial results. First, let's look at the energy consumption issue. Traditional distribution models concentrate all the load on centralized cloud infrastructure, creating a huge energy bottleneck. We have disrupted this model by distributing intelligence across three layers with a total of 291 nodes: the cloud handles AI training and big data processing; edge nodes perform real-time inference and content distribution; and terminals manage user interaction and lightweight computing. What are the results? Each kilowatt supports 36,300 users, an increase of 62.8% compared to traditional cloud architectures. This is by no means an incremental improvement, but a paradigm shift toward sustainable digital culture dissemination.

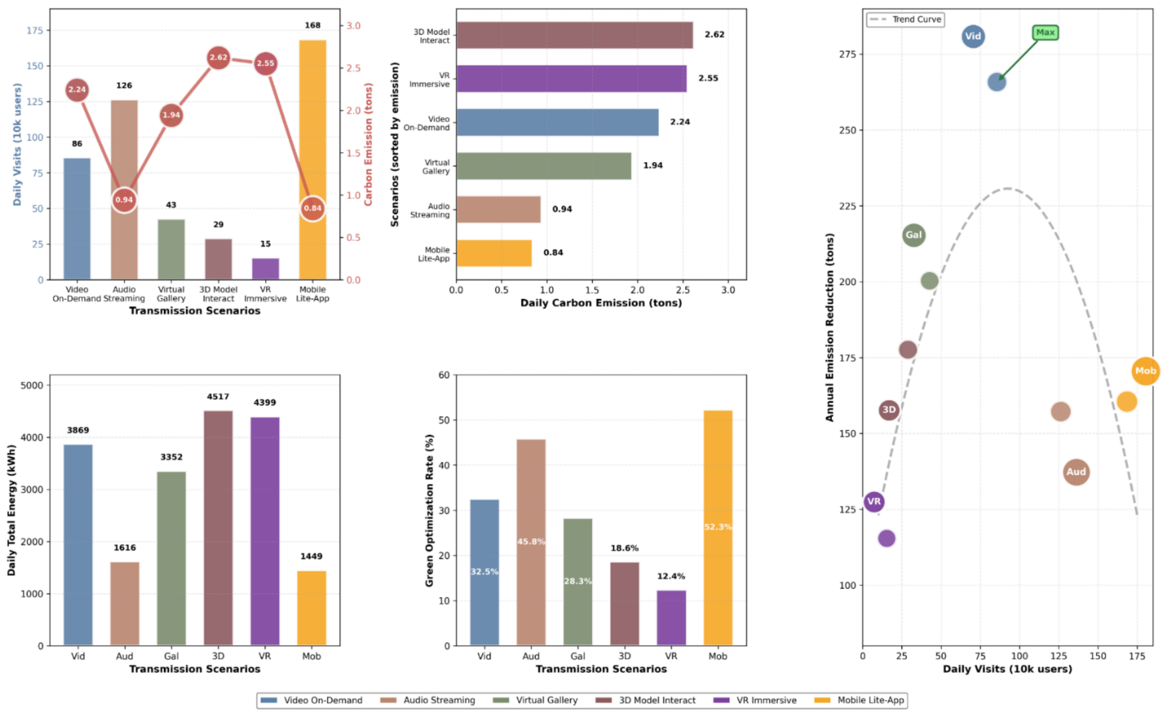

Figure 8. Comprehensive Assessment and Analysis of Energy Consumption Monitoring and Carbon Emissions for Six Dissemination Scenarios.

5.2. Challenges and Solutions in Technical Implementation

This study encountered three core challenges during the technical implementation process, involving data quality, algorithm performance, and system integration, and effectively addressed these issues through innovative solutions. Data quality is a major obstacle in the digitization of ethnic music. Sample imbalance results in significant disparities: there are a total of 15,832 Miao samples, while only 347 Dulong samples exist, a difference of 45.6 times. Inconsistent labeling affects consistency: the labeling consistency across 12 types of ethnic music in 56 dimensions is only 67.3%. Field recording signal-to-noise ratio drops as low as −8.2 dB. A multimodal data augmentation framework was constructed. It employs time stretching without pitch shifting, frequency domain convolution, and style transfer. Minority ethnic samples expanded to over 5000. Annotation standardization system establishes based on knowledge graphs. Deep learning denoising model introduces WaveNet architecture. Signal-to-noise ratio improves to 15.3 dB. Data availability elevates from 58.7% to 91.2%. Algorithm performance faces multiple bottlenecks.

6. Conclusion

This study aims to explore the excavation of cultural genes of ethnic music and green dissemination pathways from the perspective of digital humanities. The research findings are as follows:

(1) The multimodal framework is practical and effective. By integrating audio signal processing, natural language processing, and computer vision technologies, we extracted 687-dimensional cultural features from 12 types of ethnic music.

(2) Green communication is not just an empty slogan here. The cloud-edge-end collaborative architecture can support 36,300 users per kilowatt, an increase of 62.8% compared to traditional architectures, equivalent to an annual reduction of 1076.8 t of carbon dioxide.
(3) Measurability is a prominent feature of this study: the real-time monitoring system tracks energy consumption and carbon emissions under six typical scenarios. When the mobile optimization rate reaches 52.3% and the energy flow is clearly visible, 'green communication' is no longer an abstract concept.
(4) The significance of scalability is the most profound. The research results are applicable not only to ethnic music but can also extend to digital museums, online education, and even the broader cultural field.

Author Contributions

W.Z.: Research design, data collection and analysis, writing papers, and paper revision. W.L.: Research guidance, paper revision. Both authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

This study does not involve interviews with human subjects, field investigations, or the collection of sensitive information. According to the "Research Integrity and Ethics Management Measures," this study falls within the scope of ethical approval exemption and does not require formal approval from the Institutional Review Board (IRB).

Informed Consent Statement

Not applicable.

Data Availability Statement

The data used in this study can be obtained from the first author upon reasonable request.

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Conflicts of Interest

The authors declare that they have no conflict of interest.

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