International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp.1-12

https://doi.org/10.70917/ijcisim-2026-0092
Article

A Study on the Dissemination and Acceptance of Film Music in Different Cultural Contexts Based on Big Data Analysis

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Abstract: This study employs big data analysis technology, combined with social network analysis and agent-based communication models, to explore the dissemination mechanisms and acceptance differences of film music across diverse cultural contexts. "Work-to-work" and "user-to-user" communication networks are constructed, with network structural characteristics quantified using metrics such as degree centrality and intermediate centrality. Agent-based models simulate individual communication behaviors to reveal the influence of communication intent and relationship strength on communication efficiency. Empirical analysis using multi-source data reveals that an individual's status within their group is positively correlated with their dissemination behavior, and relationship strength is associated with the scope of music dissemination. As age increases, the proportion of individuals who find film music just barely acceptable gradually increases (10% and 16% for young adults, 16% for middle-aged adults, and 26% for the elderly), while the proportion who find it completely unacceptable also gradually increases (0% and 8% for young adults, 10% for middle-aged adults, and 14% for the elderly). The acceptability of film music varies little across cultural environments, with respondents from all four cultural environments reporting acceptability rates of over 80% for the example film music.

Keywords: film music; social network analysis; agent-based communication model; communication acceptability

1. Introduction

Big data, cloud computing, and other cutting-edge internet technologies have brought about revolutionary changes to many aspects of our lives [1-3]. In the realm of music, particularly the rapidly growing field of digital music, there is a strong likelihood that it will transform the dissemination methods and channels of film music [4-5]. Digital music stored in digital formats primarily spreads through the internet, with its most notable feature being that the quality of the musical work remains unchanged regardless of how many times it is played or downloaded [6-7]. This characteristic enables digital music to adapt to the demands of internet development, completely breaking free from traditional music storage media. Music dissemination based on big data analysis primarily encompasses two aspects: music recommendation and music recognition [8]. Music platforms collect real-time user behavior data, such as download information, through user IDs and mobile clients, analyze and mine the connections and characteristics within these data, and precisely recommend corresponding tracks to different end-users [9-10]. Through intelligent algorithms, features can be effectively extracted from the original waveform music, analyzed, and automatically matched with the most similar music works, thereby achieving music recognition [11-12].

The massive volume of data continues to drive the development of music data mining and recommendation research. Literature [13] constructs a recommendation algorithm based on deep belief neural networks, using hidden semantic models to extract users' preference features for hidden factors and analyzing the weights of music works on these hidden factors. Experiments demonstrate that the recommendation algorithm combining deep belief neural networks exhibits excellent recommendation performance for music. The music recommendation system proposed in [14] analyzes users' access history to determine their preference for music groups, then combines recommendation algorithms to achieve personalized recommendations of music that users prefer. The effectiveness of the proposed method was validated through a series of experiments. Literature [15] compares the performance of four algorithms—SVM, KNN, ANN, and ID3 classifiers—and their combination algorithms in music recognition. The study finds that the fusion model of SVM and ANN achieves better classification results for music emotion expression. Literature [16] extracted sound features from different datasets, combined wavelet coefficient histograms with music features, and used the multi-class extension of support vector machines to achieve an accuracy rate of over 75% in music information retrieval. Additionally, the semi-supervised learning algorithm used in the study improved the accuracy rate of music lyrics and sound recognition to over 70%.

Music recommendation and music recognition have expanded their dissemination channels and effects in the mass market. Literature [17] utilized a convolutional neural network to construct a classical music recommendation algorithm model. When the model's hidden layer dimension was 192 and the learning rate was 0.001, the model achieved optimal recommendation performance after 24,000 training iterations. By expanding the market audience for classical music through the recommendation system, the dissemination effect was enhanced. Literature [18] developed a music score recognition system using music score image enhancement, note recognition, and automatic recognition conversion technology. This system facilitates public music exchange and interaction through digital media, effectively promoting the digital dissemination of music.

The widespread application of big data and internet technologies in music dissemination has enabled music sharing, which represents the future direction of music dissemination [19]. However, research on the dissemination of film music across different cultural contexts remains limited, and further exploration is needed in the future.

This paper first reviews the core indicators of social network analysis and designs an agent-based music dissemination model. It analyzes the composition of two types of agents, namely music dissemination environment agents and music dissemination agents, and realizes music dissemination through music information dissemination interaction rules. Combining multi-source big data, it constructs a dissemination network from two dimensions. Through centrality analysis and relationship strength quantification, it reveals the influencing mechanisms of music dissemination effectiveness. Relying on questionnaire surveys, it examines the differences in dissemination capabilities of the model among different age and cultural background groups.

2. Social network Analysis Theory

2.1. Degree of Centrality

If an actor has direct relationships with many other actors, that actor occupies a central position and thus wields greater power. Actors in central positions often have multiple connections with others, whereas actors in peripheral positions do not. Under this framework, the degree centrality of a node can be measured solely based on the number of nodes directly connected to it (the degree of the node in an undirected graph, or the in-degree and out-degree of the node in a directed graph), which is known as the node's degree centrality. The degree centrality of an actor x can be categorized into two types: absolute centrality and relative centrality.

The calculation of absolute centrality is shown in Equation (1), which represents the number of nodes directly connected to node n_i. If a node has the highest degree, it is said to be at the center of the social network. In the sense of being "closely connected" to others, we say that the actor corresponding to this node is a central figure and thus holds the greatest power.

$$C_D(n_i) = d(n_i) = \sum X_{ij} \tag{1}$$

where the value of X_{ij} is either 0 or 1, with 1 indicating that actor j has a relationship with actor i and 0 indicating no relationship. For weighted graphs, centrality is represented by the sum of the edge weights between nodes, i.e.,:

$$C_D(n_i) = I(n_i) = \sum W_{ij} \tag{2}$$

where W_{ij} represents the weight of the edge connecting nodes i and j.

In fact, degree-based centrality measures consider the following question: How is a node connected to other nodes in its local environment? Since this measure is based on the number of nodes directly connected to the node and ignores indirectly connected nodes, the measured centrality is also called "local centrality." This measure can also be used to measure degree centrality in directed graphs. In this case, each node has two local centrality measures: one corresponding to the in-degree and the other to the out-degree. Therefore, local centrality can also be measured in directed graphs, but there are two types of measurements: internal centrality and external centrality, corresponding to "in-degree" and "out-degree," respectively.

There is a major limitation to measuring the centrality of a node using absolute centrality, namely that comparisons of centrality values are only meaningful among members of the same graph or among graphs of similar scale. Additionally, a node's degree depends on the scale of the graph. This is because when the scales of different graphs are different, the local centrality of nodes in different graphs cannot be compared. In other words, this measure reflects only local centrality and does not take into account the structural characteristics of the graph. Therefore, comparing centrality solely based on a node's degree may lead to misunderstandings. For example, a core node with a degree of 25 in a graph with 100 nodes is not as central as a core node with a degree of 25 in a graph with 30 nodes.

$$C_D' = \frac{d(n_i)}{n-1} \tag{3}$$

The relative measure of local centrality refers to the ratio of a point's absolute centrality (actual degree) to the maximum possible degree of nodes in the graph, as shown in Equation (3). In an undirected graph with n nodes, the maximum possible degree of any point is always $n-1$. Therefore, in a graph with 10 points, a degree of 6 means a relative centrality of 6/(10-1) = 0.66.

In the equation, n is the number of nodes in the network. Similarly, we can extend Equation (3) to weighted graphs, with the calculation formula as follows:

$$C_D' = I(n_i) / I_{\max} \tag{4}$$

The numerator $I(n_i)$ represents the sum of the edge weights between a node and all its adjacent nodes, while the denominator $I_{\max}$ represents the maximum edge weight in the graph. Thus, relative centrality is a normalized measure of absolute centrality.

It can be used to compare the centrality of nodes in networks of the same type but different sizes.

2.2. Intermediate Centrality

Intuitively, if an actor is located on many communication paths, it can be assumed that this person occupies an important position because they have the ability to control interactions between other actors. Individuals in such positions can influence groups by controlling or distorting the transmission of information. Therefore, another metric for characterizing an actor's individual centrality is intermediate centrality, which measures the extent to which an actor controls resources. If a node is on the shortest path between many other node pairs, we say that the node has a high intermediate centrality. In this sense, it acts as a bridge connecting other nodes.

If an actor is positioned between multiple pairs of actors, their degree is generally low. This relatively low-degree node may play an important "intermediary" role and thus occupy a central position in the network. An example of intermediate centrality is shown in Figure 1. In Figure 1, nodes G and M are located between many pairs of nodes. Since intermediate centrality measures the extent to which an actor acts as an "intermediary" or controls others, G can be viewed as an intermediary between actors centered around B and those centered around A, while M also serves as an intermediary between B's neighbors and C's neighbors.

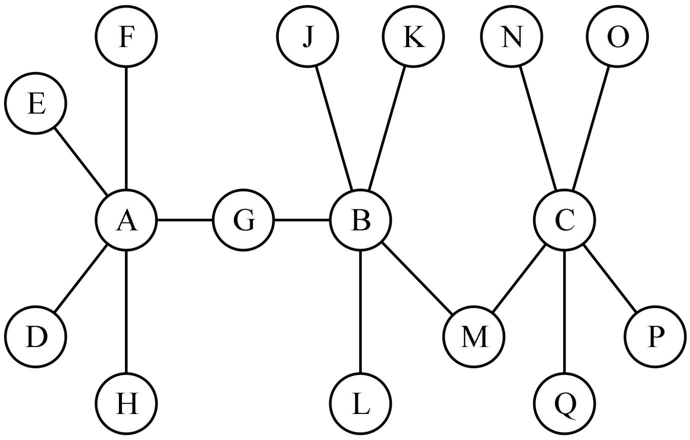

Figure 1. Schematic diagram of the central centrality.

The formula for calculating absolute central tendency is as follows:

$$C_B(n_i) = \sum_{j<k} g_{jk}(n_i) / g_{jk} \tag{5}$$

g_{jk} is the number of shortest paths from agent j to agent k, and $g_{jk}(n_i)$ is the number of paths on the shortest path from agent j to agent k that include agent i. Standardizing the absolute intermediate centrality yields the relative intermediate centrality. The calculation methods for the relative intermediate centrality of undirected graphs and directed graphs are given by Equations (6) and (7), respectively.

$$C_B^{'}(n_i) = C_B(n_i) / C_{\max} = 2C_B(n_i) / (n-1)(n-2) \tag{6}$$

$$C_B^{'}(n_i) = C_B(n_i) / C_{\max} = C_B(n_i) / (n-1)(n-2) \tag{7}$$

Among these, $C_{\max}$ represents the maximum possible value of the intermediate centrality of a node in a graph. For example, in an undirected star network with n nodes, the maximum possible value of the intermediate centrality of a node is (n-1)(n-2)/2. In a directed star network with n nodes, $C_{\max}$ is (n-1)(n-2).

The above calculation methods are all for unweighted graphs. For weighted graphs, these formulas still apply to the calculation of node intermediate centrality.

3. Music Dissemination Model Based on Intelligent Agents

The process of music information dissemination is similar to that of viral transmission. When music information disseminators carry out music information dissemination, music information recipients can receive the music information and ultimately become new music disseminators. However, music recipients may also choose not to receive music dissemination and become immune. Therefore, in this paper, when music is disseminated, the disseminators in the music dissemination intelligent agents are set as C, the recipients are set as D, and the immune individuals are set as E. Let the average ratio of music dissemination agents receiving music information per unit time be α, the ratio of music dissemination agents rejecting music information per unit time be β, and the average ratio of music dissemination agents receiving music information per unit time be j. Then:

$$\frac{dC}{dt} = -\alpha jC \tag{8}$$

$$\frac{dj}{dt} = \alpha jC - \beta_j \tag{9}$$

$$\frac{d\beta}{dt} = \beta_j \tag{10}$$

In the formula, d/dt indicates differentiation.

3.1. Model Assumptions

(1) In the music dissemination environment, there is only one source of music information dissemination, and this source is a member of the music dissemination environment. When disseminating music information, this member disseminates music to nearby music dissemination agents.

(2) The music information transmission time is divided into units, and within a single transmission time unit, music transmission between music transmission agents occurs at most once.

(3) The initial number of nodes in the music transmission environment, the degree of transmission willingness, the information value parameter, the adjustment coefficient, and the status of the nodes are all known.

3.2. Music Communication Intelligent Agent Class

According to the interaction process of music propagation agents in the music propagation environment, this paper sets the attributes of music propagation agents, including the degree of music propagation intention, propagation probability, repropagation probability, propagation times and self-level.

Degree of Propagation Intention: Describes the willingness of the music propagation agent j to disseminate musical information at the moment of e. After the implementation of music information dissemination, the function of the degree of dissemination intention is as follows:

$$\varpi_j(e)=\varpi_j(e-1)+\phi\cdot(d^{f-fC}-1)\cdot[\varpi_j(e-1)\cdot\varpi_j(e-1)] \tag{11}$$

In the equation: the willingness of music information recipients to spread music information is set as $\varpi_j(e)$; ϕ represents the music information value parameter, $\phi\in[0,1]$; the music information spread willingness decay function is set as $(d^{c-cC}-1)$, where eC represents the number of times the music information has been spread.

Propagation probability: Describes the probability of a music propagation agent achieving music information propagation at time e in the music propagation environment. To reduce model complexity, $q_1(e)$ is used to describe the propagation probability function. When implementing music information propagation, the probability function for the propagator successfully propagating is:

$$q_1(e)=1-(1-\varpi_j) \tag{12}$$

In a music dissemination environment, when music dissemination agents carry out music dissemination, the probability of successful dissemination is primarily affected by differences in the degree of dissemination willingness between the disseminator and the recipient. Since the degree of dissemination willingness varies, the dissemination probability function also exhibits variability.

Re-transmission probability: Describes the probability of an immune agent in the music transmission intelligent agent re-transmitting music information at time e. When transmitting music information, the probability function for an immune agent re-transmitting is:

$$q_2(e)=1-(1-\varpi_\beta) \tag{13}$$

In the equation, ϖ_β represents the transmission willingness function of immune individuals.

If music transmission agent j in the music transmission environment belongs to the immune group, then the probability of music transmission agent j transmitting again in the music transmission environment is related to its own transmission willingness. If $q_2(e)$ exceeds the set re-transmission threshold V', this music transmission agent can perform music information transmission again; otherwise, it will not perform music information transmission.

Number of transmissions: Describes the number of times a music transmission agent in the music transmission environment performs music information transmission with other music transmission agents at time e. This paper sets it as $M(e)$.

Self-rank: Describes the rank of the music propagation agent in the music propagation environment, denoted as $H(e)$. $H(e)=\{1,2,3,4,5\}$ When the music propagation agent interacts with other music propagation agents in the music propagation environment, the interactions between itself and other agents have a decisive influence on the value of $H(e)$; if $H(e)=5$, it indicates that the music propagation agent has the highest rank in the music propagation environment.

3.3. Music Distribution Environment

In this paper, we set the attribute of the music communication environment category as engagement.

Participation describes the existence of music dissemination in the music dissemination environment at moment e, which is set as $D(e)$, and the value of $D(e)$ is either 0 or 1. If $D(e)=1$, it means that there is music information dissemination in the music dissemination environment at moment e , and $D(e)=0$, it means that there is no music information dissemination in the music dissemination environment at moment e.

3.4. Propagated Interaction Rules between Classes of Intelligences

When music is transmitted between music transmission agents, transmitter j transmits music to nearby music transmission agent i . If the transmission willingness of j is greater than that of i , and the probability of successful transmission q_1 is not less than the set transmission threshold V , then music transmission agent i is a new transmitter; if the music information is rejected, then music transmission agent i is immune. The transmission probability q_1 between music transmission agents is influenced by the transmission willingness levels of both parties involved in the transmission of music information.

If music propagation agent i receives music information propagation, its propagation willingness level is calculated using the propagation willingness level function, then the propagation count $M_i(e)=M_i(e-1)+1$.

When music-spreading agents interact with the music-spreading environment, the music-spreading environment generally has a significant influence on the spread of music information. If music-spreading agent j spreads music information to nearby music-spreading agent i , and j 's own level is less than a specific threshold $V(e)$, then the music-spreading environment in which the music-spreading agent resides contains music information; otherwise, the music-spreading environment does not contain music information.

If the music propagation environment contains music information, it will propagate the music information to multiple music propagation agents. If $q(e)$ is not less than the set propagation threshold V , the music information receiver becomes a music information propagator. If it refuses to receive the music information, the music propagation agent is classified as an immune agent. The probability of a music propagation agent receiving music information propagated by the music propagation environment is primarily influenced by the agent's own propagation intention level.

4. Empirical Research on the Dissemination and Acceptance of Film Music in Different Cultural Contexts

As an important medium for cross-cultural communication, film music's dissemination effectiveness and acceptance levels reflect the aesthetic preferences and social interaction characteristics of different cultural contexts. In the context of globalization and digitalization, the dissemination of film music has transcended geographical boundaries, forming a complex cross-cultural network. However, existing research has primarily focused on analyzing musical characteristics within a single cultural context, with limited systematic exploration of dissemination mechanisms and acceptance differences in multicultural settings. This study, based on the previously proposed social network analysis and agent-based communication model, combines multi-source data to conduct empirical research, systematically exploring the dissemination characteristics and acceptance differences of film music across different cultural contexts. The research data includes user behavior data from music platforms, metadata from academic databases, and cross-cultural survey data. Through social network analysis tools and statistical analysis software, quantitative validation is achieved to ensure the scientific rigor and reproducibility of the conclusions.

4.1. Social Network Analysis

Music dissemination is essentially the evolutionary process of a relational network formed through interactions between nodes (works and users). This study constructs a social network from the two dimensions of “work-work” and “user-user” to reveal the underlying logic of music style evolution and user social behavior.

4.1.1. Works-Works

The construction of the music style temporal evolution network is based on publicly available music playback data from the Spotify platform between 2000 and 2024, with the sample covering the top 5,000 most-played pop music works globally. Natural language processing technology is used to extract style tags for each work. The music style temporal evolution network is shown in Figure 2, where the network reflects temporal progression from left to right and the associated issues. A1, A2, and A3 belong to jazz, A4, A5, and A6 belong to Dingbengxiang music, A7, A8, A9, and A10 belong to country music, A11, A12, and A13 belong to rock music, and A14, A15, and A16 belong to blues music.

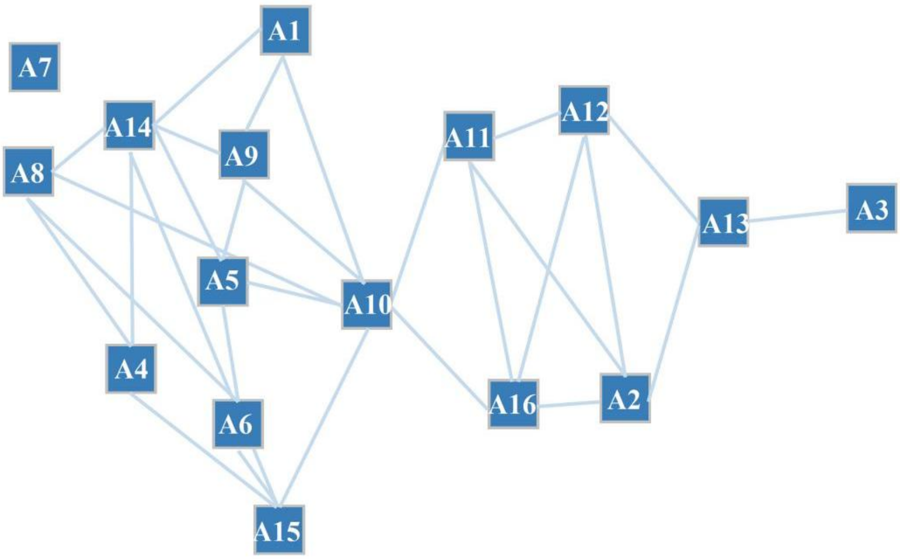

Figure 2. Network of Diachronic Changes in Music Styles.

4.1.2 User-To-User

The data for the user-to-user music social network is sourced from user interaction data from Douban Music Groups between 2020 and 2025, including comments, mentions, and mutual follows, with a total of 1,500 valid user nodes obtained. Part of the user music social network is shown in Figure 3. Figure 3 reflects the music social relationships of users with different attributes. Red indicates male gender, and blue indicates female gender. Squares represent practice-oriented (professional) master's degrees, while triangles and circles represent theory-oriented (academic) master's/doctoral degrees. The direction of the arrowhead indicates that the user represented by the starting point believes they will have music-related interactions with the user represented by the destination point. The more arrows pointing to a node, the higher its reputation. The more arrows a node sends out, the higher its influence. “Reputation” and “influence” are important metrics in centrality analysis. The numbers on the lines indicate the strength of the musical interaction relationship, for example, the strength of U1 pointing to U7 is 2.0, and the strength of U2 pointing to U12 is 5.0. The layout of the points in this diagram uses “Non-metric MDS of Geo Distances,” meaning that user nodes that are more similar tend to cluster together. In other words, this community map seems to have a social “music map” effect, allowing us to observe group clustering and classification phenomena within the overall structure. In summary, this diagram visually represents a wealth of data.

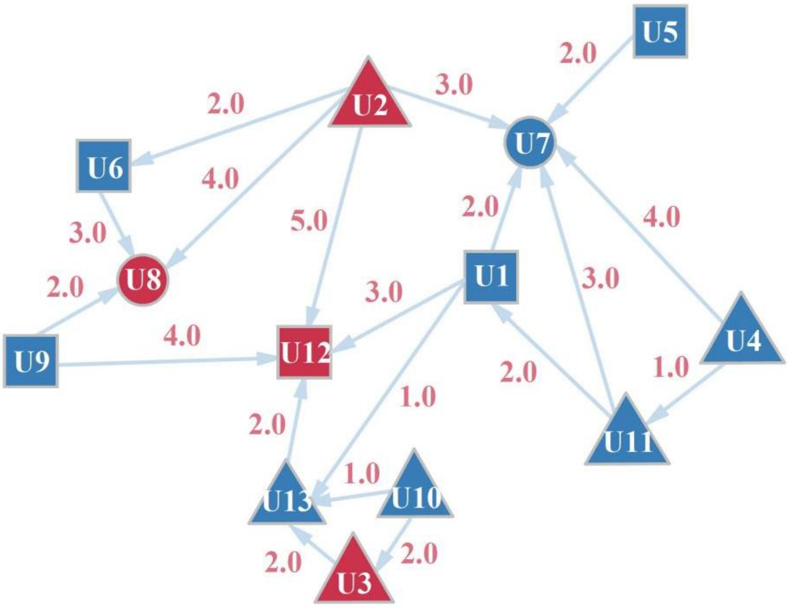

Figure 3. User music social Network.

4.2 Evaluation Indicator System Based on Centrality and Influence Analysis

Centrality analysis is a key focus of social network analysis. This method is used to analyze the influence, reputation, power, and status of individuals or organizations as nodes in a social network. Given that the community graphs in this study are predominantly "directed graphs," evaluations of influence and prestige are conducted separately. Centrality encompasses various types, and for the commonly used degree centrality, we can intuitively assess it based on the community graph. In a community graph, the more edges connected to a node, the higher its degree typically is. The conventional music evaluation system in the music industry is the music chart, and most music single charts employ degree centrality algorithms.

Given the prominence of "decentralization" and postmodernism in contemporary art evaluation, this study focuses not on the author-centric or work-centric perspectives but on the user-centric perspective. Thus, users as opinion leaders become the focal point of chart research. If a "two-pole dissemination model" is prevalent in the social spaces of digital music platforms, then a comparative study of single charts and social music charts is meaningful, as the latter takes into account the role of opinion leaders. This paper sets the scores of social charts as the Y-axis and the scores of single charts as the X-axis, plotting the relationship between the correlation of single charts and social charts and the strategic matrix, as shown in Figure 4. The direct effect in the lower right quadrant is evident, but the "aftermath" of the spread is insufficient. While the upper left quadrant may initially only be accessible to a small number of people, the spread effect driven by these individuals is significant. Figure 4 compares single charts and social music charts, providing a basic reference model for evaluating music spread effects.

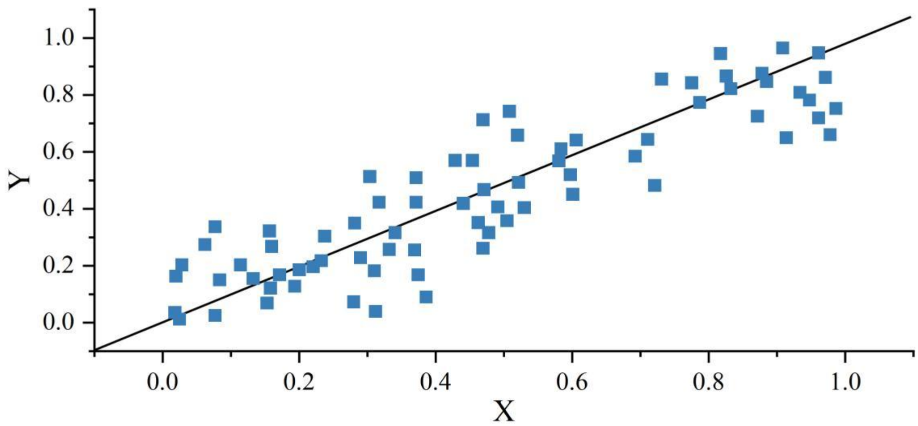

Figure 4. Singles list, social list correlation and strategy square matrix.

4.3 Relationship Strength Impact Analysis

Relationship strength reflects the depth of interaction between nodes in a social network and directly influences the willingness and effectiveness of information dissemination. This section explores the moderating effect of relationship strength on music dissemination behavior by quantifying the strength of relationships between users. In the music dissemination space, the absolute central point (10, 10) is selected as the crowd central point, (12, 12) as the relative central point, (1, 1) as the absolute edge point, and (1, 10) as the relative edge point. The distance from each grid point is used to represent the proximity, assuming that among all selected groups, only one individual is unwilling to engage in music dissemination activities. Analysis is conducted from four perspectives: absolute central point, absolute peripheral point, relative central point, and relative peripheral point. Fifty calculations are performed within the space, and the changes in the target's influence on centrality are shown in Figure 5. The status of individuals within their respective groups is positively correlated with their dissemination behavior, and the realization cycle exhibits balanced characteristics. This characteristic influences the centrality of the overall music dissemination efficiency. Under the premise of a balanced realization cycle, the influence of core individuals within the crowd on music dissemination behavior at each time point is significantly greater than that of peripheral individuals.

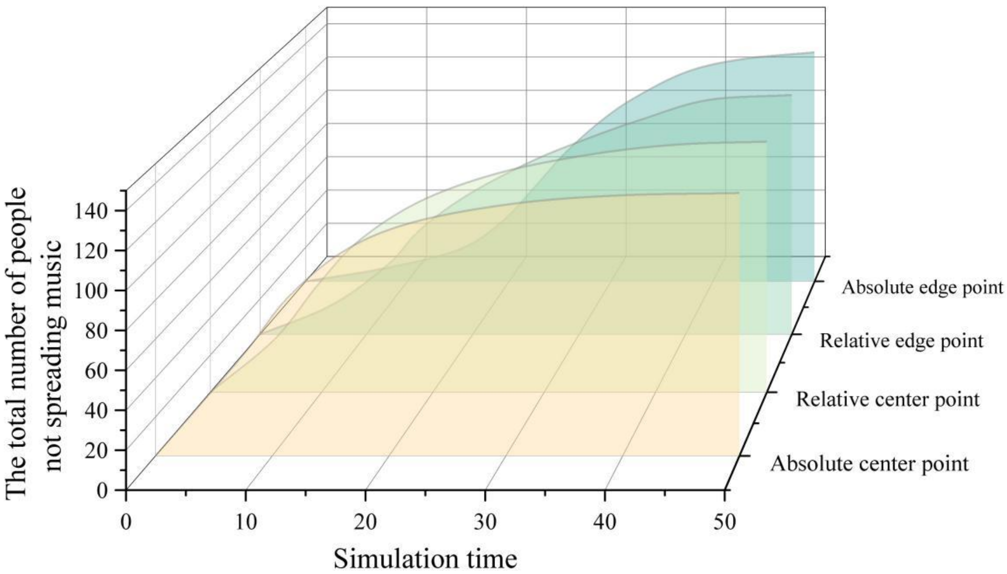

Figure 5. Changes in the effect of targets on centrality.

The changes in the impact of relationship strength on music dissemination are shown in Figure 6. There is a significant relationship between music dissemination patterns and the strength of relationships between individuals and the general public. Relationship strength is related to the scope of music dissemination. Given the sense of trust between individuals and groups, individuals are more likely to trust groups and engage in personal music dissemination behavior.

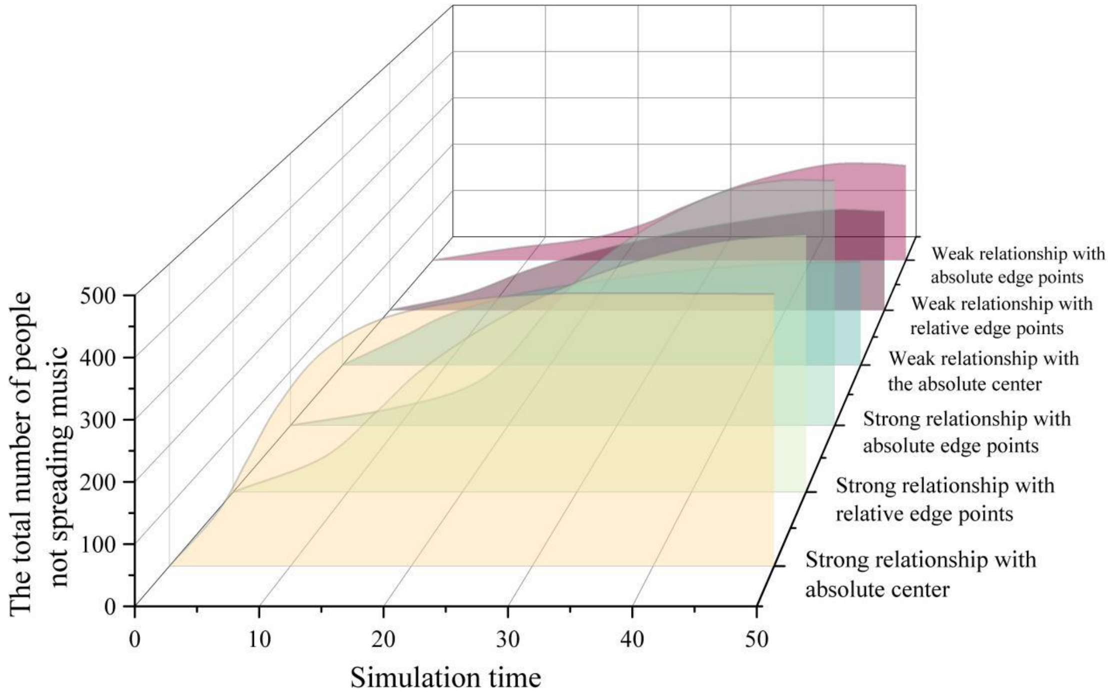

Figure 6. Changes in the influence of relationship strength on music transmission.

4.4 User Acceptance Analysis

User acceptance is the ultimate goal of music dissemination, which is influenced by multiple factors such as cultural background, age, and living environment. This study selected a well-known film soundtrack and used the proposed model to conduct a music dissemination experiment. A questionnaire survey was used to quantitatively analyze the differences in acceptance among different groups. The questionnaire data was collected using stratified sampling, and a total of 1,000 valid questionnaires were obtained, with an effective recovery rate of 83.3%.

4.4.1. Age

Based on the questionnaire data, the music acceptability voting data for respondents of different age groups is plotted as shown in Figure 7. Among young adults, the proportion of votes indicating that the example film music was completely acceptable was 52% and 32%, higher than the 26% for middle-aged adults and 24% for older adults. As age increases, the proportion of votes indicating that the example film music was just barely acceptable gradually increases (10% and 16% for young adults, 16% for middle-aged adults, and 26% for older adults). As age increases, the proportion of respondents who rated the acceptability of the example film music as “completely unacceptable” gradually increases (0% and 8% for young adults, 10% for middle-aged adults, and 14% for elderly adults). That is, as age increases, the proportion of respondents who perceive the example film music as unacceptable gradually increases, while the proportion who find it acceptable generally shows an increasing trend. From this, it can be concluded that young respondents have a higher level of acceptability for the example film music compared to older respondents.

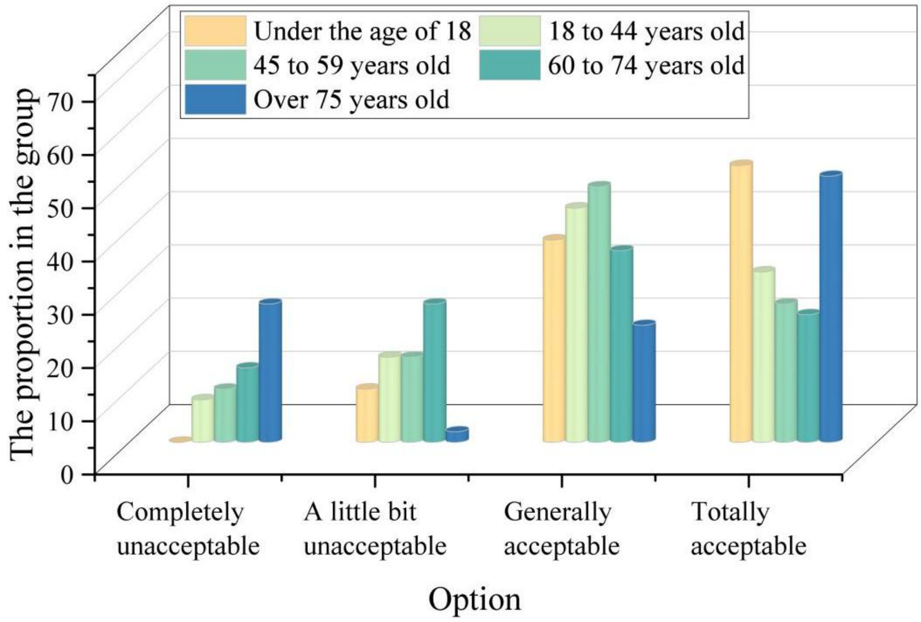

Figure 7. Music acceptability in different age groups.

4.4.2. Cultural Environment

Statistical analysis was conducted to determine the cultural environment of each respondent, categorizing them into four groups: S-S (born in the south and living in the south), S-N (born in the south and living in the north), N-N (born in the north and living in the north), and N-S (born in the north and living in the south). Based on the questionnaire data, the music acceptability voting data for respondents from different cultural environments were plotted as shown in Figure 8. The acceptability of the example film music did not vary significantly across cultural environments, with respondents from all four cultural environments achieving acceptability rates of over 80% for the example film music.

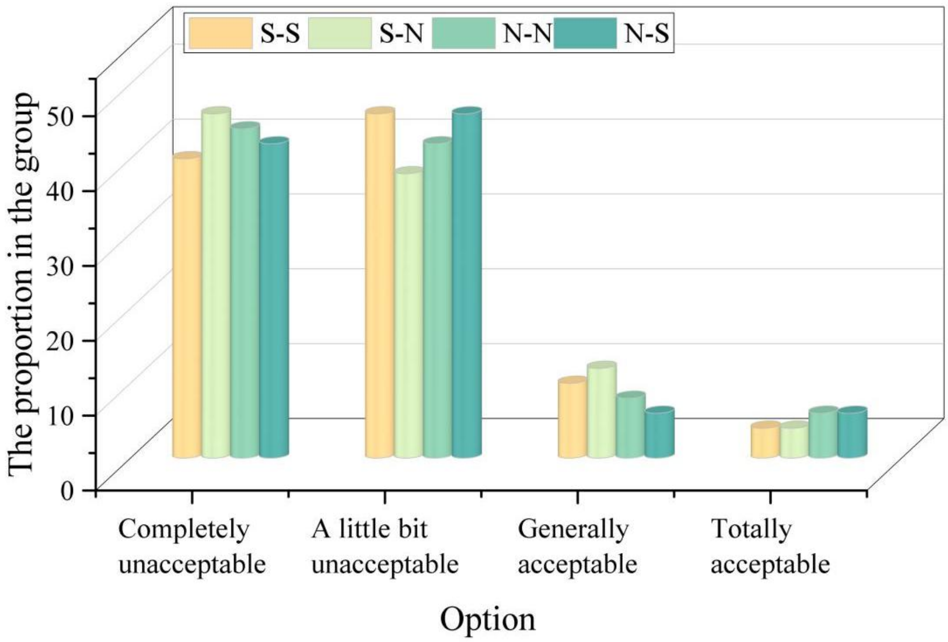

Figure 8. Music acceptability in different cultural environments.

5. Conclusion

This study systematically explores the dissemination mechanisms and differences in acceptance of film music across different cultural contexts by integrating social network analysis with an agent-based communication model.

(1) The status of individuals within their groups is positively correlated with their dissemination behavior, and the realization cycle exhibits balanced characteristics, which influence the centrality of the overall music dissemination efficiency. The strength of the relationship between music dissemination patterns and individuals is significantly correlated. Relationship strength is associated with the scope of music dissemination, as trust between individuals and groups encourages individuals to trust the group and engage in personal music dissemination behavior.

(2) As age increases, the proportion of respondents who find the example film music just barely acceptable gradually increases (10% for young adults, 16% for middle-aged adults, 16% for older adults, and 26% for the elderly), while the proportion who find it completely unacceptable gradually decreases (0% for young adults, 8% for middle-aged adults, 10% for older adults, and 14% for the elderly). The acceptability of example film music does not vary significantly across cultural environments, with respondents from all four cultural environments reporting acceptability rates of over 80%.

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