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Cultural Engagement through Music Streaming: Social and Educational Implications of Chinese and Korean OST Recommendation Systems

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Abstract

Due to the emergence of the Chinese and Korean TV shows in the global market, there has been a surge in exposure to original soundtrack (OST) music which is commonly listened without the accompanying visuals using streaming technologies. In addition to entertainment, OSTs are significant in emotional appeals, cultural and informal learning on language and national borders. This paper examines how the algorithmic OST recommendation systems can be used to contribute to cross-cultural interaction and increase the emotional and cultural awareness of East Asian media by users. This study will be based on an emotion-sensitive, cross-linguistic recommendation system, and will investigate how music recommendations mediated by a narrative process influence discovery behavior and cultural exposure to digital space users. Sound and emotional features, multiple-language metadata, and interaction by the user are synthesized in order to investigate the influence of recommendation systems in the consumption of music in a culturally diverse environment. Using experimental assessment, emotion-sensitive and multilingual modeling are found to enhance relevance of recommendation especially in sparse and cross-cultural contexts. The implications of the findings to wider social and education OST recommendation systems include the fact, that algorithmic music curation may provide an effective tool to the cultural exchange, emotional literacy, and informal media-based learning in globalized streaming ecosystems.

Keywords: Algorithmic curation; OST recommendation; Cross-cultural communication; Emotional engagement; Informal learning; Multilingual metadata; Streaming platforms; Digital sociology

1. Introduction

1.1 Global Streaming, OSTS, and Cross-Cultural Media Consumption

The development of the worldwide digital streaming providers has fundamentally altered the method of the audience engagement with media on the basis of linguistic, cultural, and national boundaries. Over the past few years, Korean and Chinese TV dramas have become widely visible in the global arena due to the transnational circulation and increased the influence of the East Asian popular culture. In combination with visual narrative, original soundtrack (OST) music has emerged as a powerful cultural product, often consumed without regard to the television series with which it is identified. OSTs are affective frames of the storytelling process and how it is vital in determining how audience recollects it, how they experience it emotionally and how they are culturally attached to it (Cohen, 2013; Kassabian, 2001).

It has been agreed that music has been used as a tool by which people form emotional meaning and cultural identity (DeNora, 2000; Frith, 1996). In TV dramas, OSTs enhance the immersion of the narrative and help them to maintain the emotion continuity after the television showing to the audience so that listeners can re-experience cultural stories via music alone. As Chinese and Korean dramas are sold to foreign nations, their OSTs help such dramas to expose to the cross-cultural experience by expressing emotional styles, linguistic aspects, and expressions that are culturally relevant to other nations (Jin, 2016; Shim, 2006).

1.2 Algorithmic Recommendation Systems as Cultural Mediators

Algorithms recommendation systems are becoming more commonly used by streaming platforms to process massive content collections and tailor user experiences. Such systems determine the content that users view, listen to, and are emotionally involved in and affect cultural discovery and media consumption patterns. Researchers have emphasized that recommendation algorithms are not the neutral information systems and actually influence taste, visibility, and cultural exposure (Beer, 2017; Striphas, 2015).

Recommendation systems can be used in the music streaming domain to direct users toward particular emotional and cultural experience by giving preference to a particular content over others, relative to its own importance. Such systems when used with OST music can influence the way that users experience foreign language, acts of emotion, and culturally-specific storytelling. This brings significant social and educational concerns of how algorithmic curation contributes to cultural exchange, emotional literacy and informal learning by way of media interaction (Green, 2008; Bennett, 2012).

1.3 Constraints of the Currently Available Research on Music Recommendation

The current research on music recommendation systems has been dominated by performance-based research and has often focused on accuracy, scalability, and efficiency, where collaborative filtering and content-based approaches have been prevalent (Bobadilla et al., 2013; Schedl et al., 2019). Although these techniques have been postulated to be effective in the general music recommendation context, they tend to ignore the culture and emotional peculiarities of OST music. However, unlike the music typical of common popular culture, OSTs have a strong connection to storyline, emotional development, and culture, resulting in the preferences of the listeners being very context-specific and emotionally-oriented (Juslin and Sloboda, 2010).

Additionally, the lyrics of mixed languages and culturally specific manifestations of emotions are also a part of the Chinese and Korean OSTs, adding even more complexity to the situation. These features are frequently ignored by the generic recommendation systems which can support cross cultural discovery and emotional recommendations to a limited extent. This disjunctive shows that there is a need to develop frameworks that do not just focus on technical optimization but to answer the question of what recommendation systems are, in the context of the socio-technical processes that mediate the processes of cultural engagement and learning.

1.4 Research Aim and Contribution

The study will fulfill the above research limitations by exploring the role of an emotion-sensitive, multi-lingual OST recommendation system in facilitating cross-cultural communication on music streaming services. Instead of focusing on the concept of recommendations as a technical problem, the study explores the socio-technical aspects of recommendations with a recommendation system acting as a means of analysis to discuss the effects of user emotions and cultures on music recommendations.

This study shows that OST recommendation systems can be used as cultural mediating tools and informal learning by adding emotional elements, multilingual metadata, and usage patterns. This work adds to the social and educational science literature because it shows the significance of algorithmic music curation in aiding the emotional understanding, cultural exposure, and learning through the media in a globalized digital environment.

2. Literature Review

2.1 Music, Emotion, and the Cultural Meaning

It has been widely recognized that music has been one of the main channels through which human beings are affected emotionally and shape-wise and negotiate cultural identity. Music is not merely a form of entertainment, and instead, it is a social resource in the daily lives of managing emotions, building memories and identities

(DeNoro, 2000). Researchers have emphasized the fact that engagement with music is close to cultural and social context, which determine the way in which people process emotional signals and cultural discourse (Frith, 1996; Juslin and Sloboda, 2010).

In audiovisual media, music has a very important role in supporting the narrative meaning and the continuity of emotions. Soundtracks in movies and television serve the purpose of emotional pointing towards allowing viewers to interpret, stimulating emotion, and extending narrative involvement (Cohen, 2013; Kassabian, 2001). The original soundtracks (OSTs) especially are created to evoke certain emotional situations in accordance with the narration arcs, which distinguish them as opposed to the ordinary popular music. The sound, when it is listened to without visual support of the narrative, still has the emotional and cultural connotations of the track and can aid the listeners to re-experience the narrative experiences solely through sound.

2.2 OSTs & Cross-Cultural Media Consumption

The success of East Asian television dramas in the world has made the diffusion of Chinese and Korean cultural products worldwide easy. Studies of the Korean Wave (Hallyu) have indicated that culture is propagated through media content, such as music, and media content is used to exercise soft power, influencing the perceptions and affective encounters of the foreign audience with the foreign cultures (Jin, 2016; Shim, 2006). This has been experienced in the emergence of Chinese dramas in the global scene where OSTs are employed to convey cultural language and emotions beyond the local borders.

Cross-cultural environments are particularly effective in OSTs as the expression of emotions through music is not frequently hampered by language. This is because listeners can listen to affectively resonant soundtrack and do not need to understand much about the lyrics of the songs and can therefore connect on an affective level and pose cultural questions. This process leads to informal exposure to language, expression of emotions and narrative conventions incorporated in media contents (Bennett, 2012). In this regard, the OST consumption can be discussed as a significant setting where the exchange of cultures and experience-based learning via digital media can be considered.

2.3 System of Algorithmic Recommendation Systems and Cultural Exposure

Algorithms The use of algorithmic recommendation systems has become more and more important in the digital streaming business to organize big content catalogs and personalize the user experience. Whereas accuracy and efficiency are generally considered in the evaluation of recommendation technologies, the social sciences have illuminated the wider cultural context in work on the topic. Active effects of algorithms on visibility, taste, and patterns of cultural consumption are given precedence by prioritizing certain content over others (Beer, 2017; Striphas, 2015).

When applied to music streaming, it is possible to note that the recommendation system does not only influence the music people listen but also influences their emotional expression to music and discovery of culturally diverse music. It has been debated by scholars whether algorithmic curation would strengthen homogeneity or cultural diversity, but it depends upon how the systems are designed and evaluated (Ricci et al., 2022). Educationally speaking, algorithmic exposure to culturally diverse music can be supportive of informal learning processes by introducing individuals to new languages, emotional styles and cultural stories through the repetition of exposure (Green, 2008).

2.4 Music Recommendation Systems: Technical Underpinnings and Flaws

Music recommendation systems studies have generally built on collaborative filtering, content-based and hybrid systems that maximize the accuracy of recommendations based on user interaction information and audio characteristics (Bobadilla et al., 2013; Schedl et al., 2019). By incorporating miscellaneous data sources, at the form of audio cues, metadata, and implicit feedback, further optimizations of system performance through multimodal and deep learning-based recommendation are accomplished (Liu et al., 2024).

Nevertheless, in modern technical solutions, music tracks are usually treated as generic entities with little consideration of the story, emotional, and cultural specificity of OSTs. The emotional representations are rarely considered as a key variable in the cultural relevance field, whereas emotion recognition in music is a studied topic (Yang and Chen, 2012; Markov and Matsui, 2020). In a similar manner, the research on multilingual recommendations has taken a preference alignment strategy across languages and did not focus much on music-specific, emotional, and narrative aspects (Li et al., 2021; Zheng et al., 2021).

2.5 Emotion-Aware and Multilingual Recommendation in Social Context

Recent interdisciplinary studies indicate that emotion-sensitive recommendation systems can enhance the user experience and relevance and could be especially effective in situations where emotion resonance is a central aspect of consumer behaviour (Wang et al., 2023). In the context of music, the emotion-conscious models have the capability of making more meaningful suggestions, as they are able to compare affective characteristics with the preferences of the listeners, assisting in the further emotional involvement of the latter.

Another factor that relates to cross-cultural content discovery is multilingual recommendation systems that allow users to browse cross linguistic content. Instead of using explicit translation, embedding-based methods allow systems to retrieve joint semantic and emotional patterns across languages (Li et al., 2021). Such strategies when implemented in relation to OST music can promote culturally inclusive practices of recommendation that facilitates access to a variety of media traditions.

Alongside these developments, relatively little has been done in terms of unified frameworks which then explore the emotional modeling, the multilingual representation, and their general social and educational implications. Current studies do not pay much attention to how the use of recommendation systems can contribute to cultural engagement, emotional literacy, and informal learning by listening to music.

2.6 Research Gap and Theoretical Positioning

The literature reviewed above reveals a clear divide between technical developments in music recommender systems and social science research on music, emotion, and cultural engagement. While OSTs are emotionally rich and culturally encoded musical artifacts, they have yet to be explored in recommendation research from a socio-technical perspective. Moreover, there are very few studies that explicitly address how algorithmic curation of OSTs may facilitate cross-cultural exposure and informal learning in streaming environments.

This research addresses this gap by introducing an emotion-aware, multilingual OST recommendation framework as a tool for understanding cultural mediation on digital music platforms. By combining insights from music psychology, cultural studies, and recommender systems research, the work advances an interdisciplinary understanding of the role of recommendation algorithms in globalised media ecosystems, particularly in shaping people's emotional engagement and cultural access.

To clarify how existing research addresses the cultural, emotional, and educational dimensions of music recommendation, Table 1 presents a comparative overview of prior studies with respect to key sociocultural requirements of OST-centric recommendation systems.

Table 1. Comparative overview of prior research and OST-centric socio-cultural requirements

Prior Research Focus	Cultural Context & Meaning	Emotional Engagement	Multilingual / Cross-Cultural Exposure	Educational / Informal Learning Perspective	Key Limitation for OST Research
General music recommender systems (Bobadilla et al., 2013;	Limited	Partial	Limited	Not addressed	Treat music as generic items without narrative or cultural grounding

Schedl et al., 2019)					
Emotion and music psychology studies (DeNora, 2000; Juslin & Sloboda, 2010)	Strong	Strong	Limited	Implicit	Do not examine algorithmic mediation or digital platforms
Film and OST studies (Cohen, 2013; Kassabian, 2001)	Strong	Strong	Partial	Implicit	Focus on narrative analysis rather than digital recommendati on
Algorithmic culture and platform studies (Beer, 2017; Striphas, 2015)	Strong	Limited	Limited	Partial	Do not address music-specific or OST-focused contexts
Multilingual recommendat ion research (Li et al., 2021; Zheng et al., 2021)	Limited	Limited	Strong	Not addressed	Lacks emotional and narrative consideration s
This study (OST-centric socio-technical framework)	**Strong**	**Strong**	**Strong**	**Explicit**	Integrates emotion-aware recommendati on with cultural and educational analysis

As shown in Table 1, existing studies tend to address technical performance, emotional analysis, or cultural theory in isolation. Few approaches integrate emotional engagement, multilingual exposure, and educational relevance within a unified framework for OST recommendation. This gap motivates the present study's socio-technical approach to examining how emotion-aware and multilingual recommendation systems can facilitate cross-cultural engagement and informal learning in digital music platforms.

3. Methodology: Socio-Technical Research Design

3.1 Research Design and Analytical Approach

This study adopts a socio-technical research design that treats algorithmic recommendation systems as both computational mechanisms and cultural mediators within streaming environments (Beer, 2017; Striphas, 2015). CK-OSTRec is used as an analytical tool to examine how emotion-aware and multilingual curation can shape user discovery, emotional engagement, and cross-cultural exposure to OST music from China and Korea.

The approach combines (i) computational modeling to operationalize emotional resonance, cultural context, and engagement, and (ii) interpretive analysis to explain what observed performance differences imply for culturally meaningful recommendation and informal learning outcomes (Green, 2008; Ricci et al., 2022).

3.2 CK-OSTRec Framework Overview

CK-OSTRec integrates four signals: audio semantics, affective (emotion) representation, cultural contextual metadata, and implicit engagement within a unified relevance-scoring mechanism. This hybrid design follows established directions in multimodal and hybrid recommender systems, adapted to the narrative/emotional specificity of OST consumption (Zhang et al., 2019; Zhao et al., 2023).

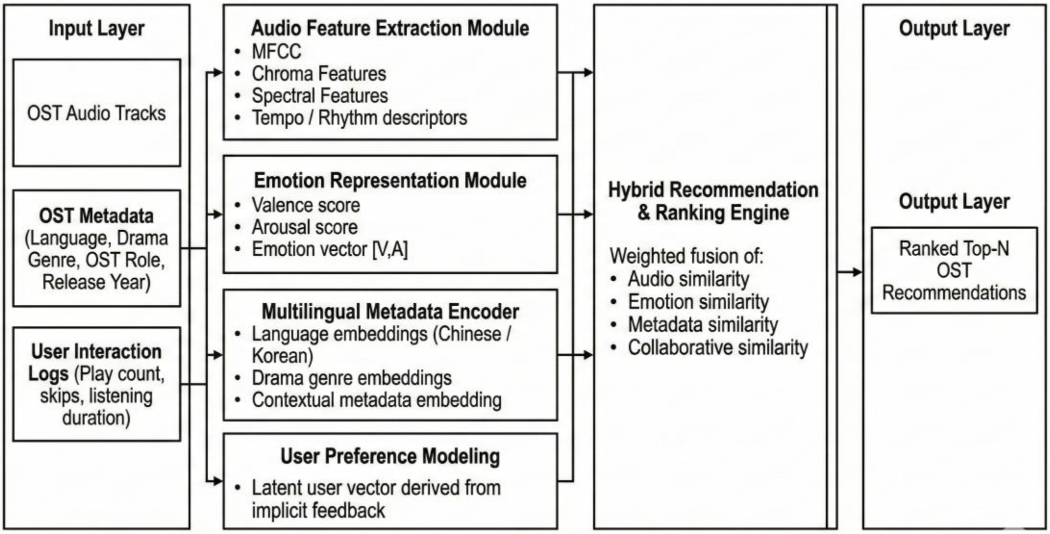

Figure 1*. Architecture of the CK-OSTRec framework, illustrating the integration of audio features, emotion representations, multilingual contextual metadata, and user interaction signals for OST recommendation.*

Algorithms do not only rank content; they structure cultural exposure by prioritizing certain emotional and multilingual pathways of discovery (Beer, 2017; Striphas, 2015).

3.3 Audio Semantics Representation

To operationalize musical cues associated with mood and narrative intensity, each OST track is represented using a normalized audio feature vector derived from standard music information retrieval practices (McFee et al., 2015) and prior audio-based music recommendation work (Van den Oord et al., 2013).

Let the normalized audio feature vector for the OST track $\boldsymbol{i}$ be:

$$\boldsymbol{A_i} \in \mathbb{R}^{\boldsymbol{d_a}}$$

Feature normalization is applied using z-score normalization:

$$\widehat{\boldsymbol{A}}_{\boldsymbol{i,j}} = \frac{\boldsymbol{A_{i,j}} - \boldsymbol{\mu_j}}{\boldsymbol{\sigma_j}}$$

where $\boldsymbol{\mu_j}$ and $\boldsymbol{\sigma_j}$ are the mean and standard deviation of the feature $\boldsymbol{j}$ across the training set. These audio representations support discovery beyond language-specific cues, which is important when OST listening is driven by mood and scene association rather than artist familiarity (Schedl et al., 2019).

3.4 Affective Representation Using Valence–Arousal Modeling

Because OST music is designed to evoke scene-level emotions, emotional characteristics are modeled using a continuous **valence–arousal** representation (Yang & Chen, 2012; Tripathi et al., 2020). For each track $\boldsymbol{i}$, the emotion vector is defined as:

$$\boldsymbol{E_i} = [\boldsymbol{V_i}, \boldsymbol{A_i}]$$

where:

- $\boldsymbol{V_i}$ denotes valence (positive–negative affect),
- $\boldsymbol{A_i}$denotes arousal (calm–excited intensity).

To estimate affective alignment between a user's inferred emotional preference profile and a candidate track, cosine similarity is employed:

$$\mathbf{Sim}_{\boldsymbol{emo}}(\boldsymbol{u}, \boldsymbol{i}) = \frac{\boldsymbol{E_u} \cdot \boldsymbol{E_i}}{\|\boldsymbol{E_u}\| \|\boldsymbol{E_i}\|}$$

This formulation aligns with emotion-aware recommendation approaches that incorporate affective signals to improve perceived relevance and emotional resonance (Wang et al., 2023; Kim & Park, 2023).

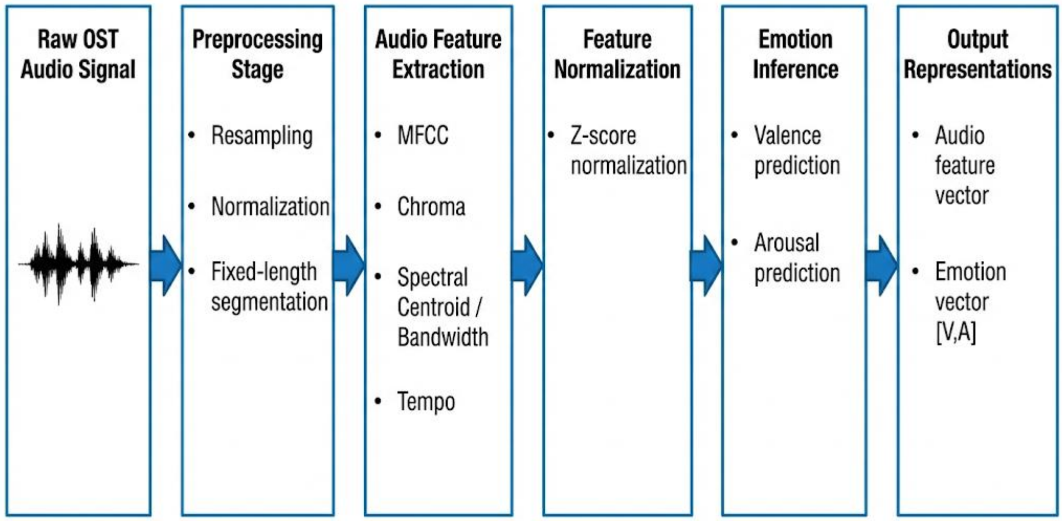

Figure 2. *Feature extraction pipeline for OST tracks, showing the processes used to derive audio features and emotion-related representations.*

Figure 2 summarizes the pipeline operationalizing emotional resonance at scale, enabling culturally meaningful recommendations across multilingual catalogs (Yang & Chen, 2012; Wang et al., 2023).

3.5 Cultural–Contextual (Multilingual) Metadata Encoding

To represent cultural and narrative context, multilingual metadata (e.g., language, drama genre, year, region, and OST role, where available) is encoded into a dense embedding. Let the metadata embedding for track iii be:

$$\boldsymbol{M_i} \in \mathbb{R}^{\boldsymbol{d_m}}$$

This encoding supports cross-lingual discovery by aligning contextual signals without requiring explicit translation, consistent with multilingual recommender design principles (Li et al., 2021; Zheng et al., 2021).

3.6 Engagement-Based User Preference Modeling (Implicit Feedback)

User preferences are inferred from implicit engagement signals (plays, skips, listening duration), consistent with large-scale streaming recommendation settings where explicit ratings are rare (Rendle et al., 2009; Covington et al., 2016). The user representation is defined as:

$$\boldsymbol{U_u} \in \mathbb{R}^{\boldsymbol{d_u}}$$

In this study, engagement-based preference modeling functions as a proxy for interest and satisfaction in emotionally or culturally resonant OST content (Cai et al., 2022; Schedl et al., 2018).

3.7 Multi-Signal Relevance Scoring and Ranking

The final recommendation score integrates audio similarity, emotion similarity, metadata similarity, and collaborative/engagement alignment into a single relevance score:

$$\mathbf{Score}(\boldsymbol{u},\boldsymbol{i}) = \boldsymbol{\lambda_1}\mathbf{Sim}_{\boldsymbol{audio}}(\boldsymbol{u},\boldsymbol{i}) + \boldsymbol{\lambda_2}\mathbf{Sim}_{\boldsymbol{emo}}(\boldsymbol{u},\boldsymbol{i}) + \boldsymbol{\lambda_3}\mathbf{Sim}_{\boldsymbol{meta}}(\boldsymbol{u},\boldsymbol{i}) + \boldsymbol{\lambda_4}\mathbf{Sim}_{\boldsymbol{collab}}(\boldsymbol{u},\boldsymbol{i})\mathbf{(4)}$$

where:

- $\boldsymbol{\lambda_1}, \boldsymbol{\lambda_2}, \boldsymbol{\lambda_3}, \boldsymbol{\lambda_4} \geq \mathbf{0}$ are weighting coefficients,
- $\sum_{\boldsymbol{k}=\mathbf{1}}^{\mathbf{4}} \boldsymbol{\lambda_k} = \mathbf{1}.$

Such weighted fusion is widely used in hybrid recommender systems to combine heterogeneous signals under sparse feedback conditions (Zhang et al., 2019; Zhao et al., 2023).

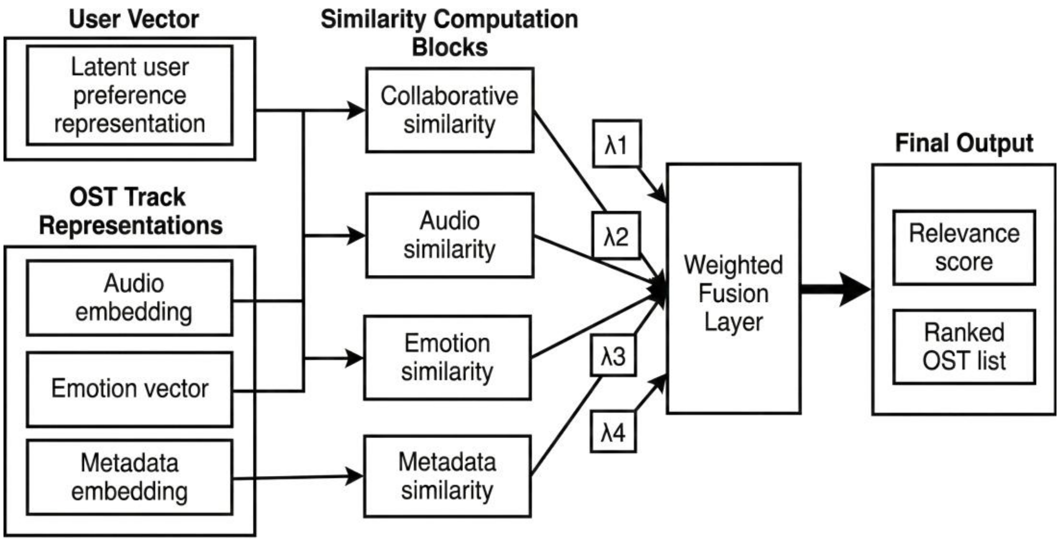

Figure 3. *Scoring and ranking framework of CK-OSTRec, depicting the combination of audio features, emotion information, contextual metadata, and collaborative similarity signals.*

Figure 3 illustrates how the fusion strategy shows multiple signals jointly shape what users are exposed to, enabling socio-technical interpretation of algorithmic curation and cross-cultural discovery (Beer, 2017; Ricci et al., 2022).

3.8 Feature Taxonomy and Operational Definitions

To improve transparency and interpretability, CK-OSTRec links computational inputs to socio-cultural constructs:

- **Audio features** → musical cues supporting similarity beyond language
- **Emotion features (valence/arousal)** → affective resonance and narrative mood alignment
- **Metadata features** → cultural and narrative context (language, genre, OST role)
- **User behavior** → engagement-based preference signals

Table 2 summarizes the complete feature taxonomy used in the proposed framework.

Table 2. *Feature Taxonomy for CK-OSTRec*

Feature Category	Feature Type	Description
Audio Features	MFCC, Chroma, Spectral	Capture timbral, tonal, and spectral characteristics
Emotion Features	Valence, Arousal	Represent affective dimensions of OST tracks
Metadata Features	Language, Genre, OST Role	Encode narrative and cultural context
User Behavior	Play count, skips, duration	Model implicit listening preferences

3.9 Ethical Considerations

This study is based on publicly available datasets and derived interaction benchmarks that do not contain personally identifiable information. There is no recruitment of direct human participants, surveys or interventions. Results are reported at the aggregate level, in accordance with privacy-preserving practices and responsible reporting.

3.10 Interpretation Strategy

The following computational evaluation findings are interpreted in a socio-technical framework to discuss what emotion-aware and multilingual modeling means for cross-cultural engagement and informal learning in streaming situations (Beer, 2017; Green, 2008). Differences between baselines and ablations are used to infer which signals (emotion, cultural context, audio cues, engagement patterns) are most important for culturally meaningful recommendations under sparse interaction settings.

Evaluation Design: Data, Baselines, and Measures

This section introduces the empirical evaluation used to assess the effectiveness of emotion-aware and multilingual modeling for improving top-N OST recommendations in sparse, cross-cultural streaming settings. Given the limited number of recommendations exposed in platform interfaces, the evaluation focuses on the quality of top-K ranking and considers improvements that better match algorithmic curation and user discovery behavior in multilingual OST catalogs (Bobadilla et al., 2013; Wu et al., 2023).

4.1 Data Sources and Benchmark

Two data components are used. First, the Free Music Archive (FMA) dataset is used as a public dataset of audio corpus supporting consistent feature extraction and reproducibility Defferrard et al. (2017). Second, a derived Chinese-Korean OST benchmark (CK-OST-Set) is adopted to represent multilingual OST discovery by aligning information at the track level with metadata describing drama/context (e.g., language, genre, year/region, and OST role, where available) and with implicit engagement traces.

Table 3 presents the dataset statistics (tracks, users/interactions, sparsity characteristics, and cold-start composition) and is included to document the evaluation setting transparently.

Table 3. Dataset Statistics Used in Experiments

Dataset / Subset	#Tracks	#Users	#Interactions	Languages	Primary Use
FMA (subset)	25,000	–	–	Multi	Audio feature learning [24]
CK-OST-Set	3,200	12,000	420,000	Chinese/Korean	Recommendation benchmark
CK-OST-Set (Cold-start split)	600	12,000	65,000	Chinese/Korean	Cold-start evaluation

4.2 Preprocessing and Representations

Audio features (MFCCs, chroma, spectral features, and tempo/beat features) are extracted using a standard MIR pipeline implemented in Librosa (McFee et al., 2015). Audio features are normalized by z-score normalization (defined in Section 3). Track emotion is encoded in a continuous valence-arousal space, which is in line with the practice of modeling emotion in music (Yang & Chen, 2012; Tripathi et al., 2020). Multilingual/cultural metadata (language, drama genre/context, year/region, OST role where available) is encoded into dense representations to allow cross-lingual alignment without explicit translation, consistent with multilingual recommendation approaches (Li et al., 2021; Zheng et al., 2021).

4.3 Baseline Methods

CK-OSTRec is compared to representative baselines in the implicit collaborative filtering, graph-based collaborative filtering, hybrid/multimodal recommendation, and self-supervised/contrastive learning baselines:

- Implicit CF (BPR-MF): implicit-feedback ranking standard strategy with Bayesian Personalized Ranking (Rendle et al., 2009).
- Graph-based CF (NGCF family): neural graph collaborative filtering propagates signal on the user-item interaction graph, often achieving better performance in sparsity cases (Wang et al., 2022).
- Hybrid/multimodal recommenders: fusion-based models, which represent common deep hybrid recommendation practice (Zhang et al., 2019; Zhao et al., 2023).
- Self-supervised / contrastive recommendation: representation learning baselines for better generalization and robustness under sparse recommendations (Sun et al., 2023).

4.4 Evaluation Protocol

A user-wise train/validation/test split is used to reflect realistic next item recommendations. Where timestamps are available, chronological splitting of interactions is used; otherwise, per-user randomized splitting is used. For evaluation, each user is associated with the candidate set, which is formed from held-out positives and sampled negatives from non-interacted items, as is standard practice for implicit-feedback evaluation (Rendle et al., 2009; Wu et al., 2023). A cold-start evaluation subset is retained to assess performance on OST tracks with few historical interactions, a common stress condition for recommendation systems in emerging or niche catalogs (Schedl et al., 2018).

4.5 Metrics

We perform a user-wise train/validation/test split (based on timestamps; the order is chronological and randomized within each user). For each user, candidates are ranked using negative sampling on the model's non-interacted items (Rendle et al., 2009). Performance is reported using Precision@K, Recall@K, and NDCG@K, which are standard measures of top-N ranking in recommender systems (Bobadilla et al., 2013; Wu et al., 2023).

4.6 Training and Implementation Settings

Models are trained using the Adam optimizer with early stopping and the NDCG@K metric on the validation set. Negative sampling is used during training and evaluation on non-interacted items, similar to implicit feedback ranking (Rendle et al., 2009). For CK-OSTRec, fusion weights (the \ lambda coefficients in the final scoring function defined in Section 3) are optimized on the validation set for balancing audio, emotion, metadata, and collaborative/engagement signals.

4.7 Ablation Study

To isolate the contribution of each signal, ablation variants are tested by removing or adding components: audio-only, audio+metadata, audio+emotion, and the full model. This design posits that affective modeling and multilingual context (as opposed to acoustic similarity and interaction-driven signals) yield measurable gains, particularly in sparse and cold-start conditions (Schedl et al., 2018; Zhao et al., 2023).

Results

This section presents the performance of CK-OSTRec using the evaluation design described in Section 4. Results cover (i) overall quality of top-K recommendations, (ii) cold-start performance in the presence of sparse interactions, and (iii) an ablation study that isolates the contribution of audio, emotion, and multilingual/context signals. Because only a few recommendations are typically consumed, we focus on top-K ranking quality (Bobadilla et al., 2013; Wu et al., 2023). A broader socio-cultural and educational interpretation is provided in Section 6.

5.1 Overall Recommendation Performance

Table 4. *Overall top-K recommendation performance*

Method	**Precision@10**	**Recall@10**	**NDCG@10**
BPR-MF	0.214	0.187	0.198
Graph-based CF	0.236	0.209	0.223
Multimodal DNN	0.258	0.231	0.247
Self-supervised RS	0.269	0.242	0.259
CK-OSTRec	**0.312**	**0.286**	**0.301**

As shown in Table 4, CK-OSTRec outperforms the baselines across all metrics, with particularly significant gains on ranking-sensitive NDCG@10. This suggests that relevant OSTs are positioned closer to the top of the list of recommendations - a crucial aspect for streaming applications where top-ranked items will receive the greatest attention (Bobadilla et al. 2013; Wu et al. 2023).

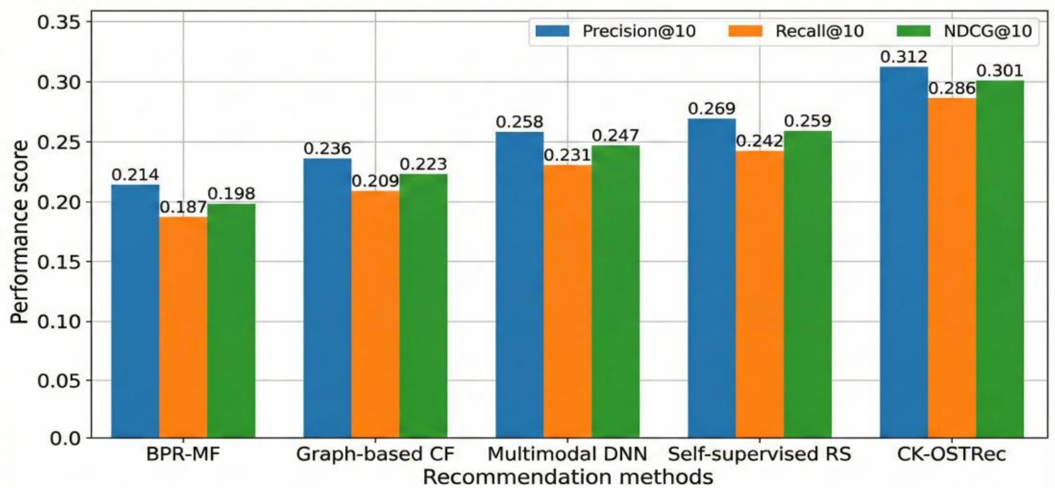

Figure 4. *Comparative performance trends across top-K recommendations.*

5.2 Cold-Start And Sparse-Interactions Performance

Table 5. *Cold-start performance on OST tracks with limited historical interactions.*

Method	Precision@10	Recall@10	NDCG@10
BPR-MF	0.141	0.123	0.131
Graph-based CF	0.158	0.139	0.147
Multimodal DNN	0.211	0.187	0.199
CK-OSTRec	**0.274**	**0.249**	**0.261**

Cold-start evaluation is crucial for OST catalogs because new drama soundtracks often have small interaction histories, which makes interaction-only approaches less effective (Schedl et al., 2018; Schedl et al., 2019). Table 5 shows that CK-OSTRec is quite robust under sparse conditions, consistent with evidence that content and auxiliary semantics (audio, emotion, metadata) help reduce the need for dense user-item histories (Van den Oord et al., 2013; Schedl et al., 2018).

5.3 Ablation Study

Table 6. Results of ablation for CK-OSTRec variants.

Variant	**Precision@10**	**Recall@10**	**NDCG@10**
Audio only	0.241	0.216	0.227
Audio + Metadata	0.268	0.242	0.254
Audio + Emotion	0.281	0.257	0.269
Full model	**0.312**	**0.286**	**0.301**

Table 6 shows incremental gains as more signals are introduced. Audio+Metadata and Audio+Emotion are better than the audio-only variant, while the full model delivers the best performance, supporting the advantage of fusion of heterogeneous signals in hybrid recommendation - especially under sparsity (Zhang et al., 2019; Zhao et al., 2023). This provides important quantitative evidence that emotion-aware and multilingual/context modeling adds value beyond acoustic similarity alone.

5.4 Summary of Empirical findings

From experiment to experiment, there are three consistencies:

- CK-OSTRec enhances the overall quality of rankings by incorporating audio, emotion, multilingual metadata, and signals of engagement (Bobadilla et al., 2013; Zhao et al., 2023).
- Cold start robustness improved over interaction-driven baselines - this indicates the importance of content and affective/contextual signals in situations where histories are sparse (Schedl et al., 2018; Van den Oord et al., 2013).
- Ablations affirm component contributions, with emotion-aware and multilingual/context modeling yielding measurable gains over partial variants (Yang & Chen, 2012; Zhang et al., 2019)

These results provide quantitative validation of the framework; Section 6 interprets their implications with respect to cross-cultural engagement, emotional resonance, and informal learning in streaming environments.

Discussion

This section explains the empirical results presented in Section 5, using a socio-technical perspective, and relates quantitative improvements in recommendation quality to broader implications for Cross-cultural engagement, emotional experience, and informal learning in streaming environments. While Precision@K, Recall@K, and NDCG@K ensure the validity of the system, the major contribution in social science and education contexts lies in the implications of those gains for how algorithmic curation influences cultural exposure and emotionally meaningful media consumption (Beer, 2017; Striphas, 2015).

6.1 The Significance of Emotion Aware Gains in OST Listening

OST listening differs from general music streaming due to its often specific, narrative-linked (e.g., emotion, scene memory) mood-regulatory preferences. The results of this study, showing improvements for CK-OSTRec and, in particular, for a ranking-sensitive measure, are encouraging, as they indicate that emotion-aware representations may be more closely aligned with users' affective intent (Juslin & Sloboda, 2010; DeNora, 2000). Valence-arousal modeling promotes emotional matching beyond coarse labels, which is important when users seek similar feelings across different dramas and contexts (Yang & Chen, 2012). In practice, more salient top-K rankings result in earlier exposure to emotionally relevant OSTs, thereby enhancing coherent affective engagement and reducing emotionally mismatched exposure.

6.2 Context Multilingual and Cross-Cultural Discovery

A concern by reviewers is whether the work has social/cultural value beyond implementation. CK-OSTRec supports the discovery of Chinese and Korean catalogs without explicit translation, and its higher performance in sparse and cross-cultural settings suggests that language, drama attributes, and OST roles serve as bridging signals, increasing exposure beyond dominant language preferences (Li et al., 2021; Zheng et al., 2021). From a diffusion perspective, algorithmic exposure can enhance engagement with East Asian media traditions by foregrounding emotionally meaningful soundtracks that convey cultural expressions and narrative conventions embedded in the culture (Jin, 2016; Shim, 2006). This strengthens the position of recommenders as gatekeepers of cultural visibility and access (Beer, 2017).

6.3 Implications for the Informal Learning Emotional Literacy

Although CK-OSTRec is not a formal educational intervention, streaming environments can support informal learning through repeated cultural exposure and affective engagement. OSTs also tend to contain linguistic cues, culturally-specific metaphors, and recurring emotional themes that may support language exposure and narrative interpretation, and emotional vocabulary development (Green 2008). When systems regularly surface emotionally consonant and culturally situated OSTs, then they can foster sustained engagement and curiosity - conditions associated with informal learning and exploratory behavior in digital environments (Bennett, 2012). Thus, the contribution is more than "better recommendations," and it is about understanding how algorithmic curation can aid in emotional literacy and cross-cultural communication through media-based engagement (DeNora, 2000; Juslin and Sloboda, 2010).

6.4 Why Robustness of cold start is socially important

Cold-start performance is not only relevant from a technical perspective but also meaningful from a social perspective. New drama OSTs can be indicative of new cultural moments, but often lack a significant presence in interaction-based systems. CK-OSTRec's improved cold-start performance suggests that affective and contextual signals reduce reliance on popularity and dense histories, thereby favoring more equitable exposure for new or niche OST items (Schedl et al., 2018; Schedl et al., 2019). This is important because when recommenders are allowed to repeat the loudest content, it can be limiting for cultural diversity and reinforcing of faith homogeneity in consumption. By enabling more effective discovery under sparse feedback, emotion-aware multilingual modeling may help surface a wider variety of culturally meaningful OSTs to promote cultural diversity.

6.5 Algorithmic Curation, Cultural Diversity, and Platform Responsibility

Social science research brings out the influence of algorithms on taste and cultural participation (curation of what is visible and repeatedly encountered) (Striphas, 2015; Beer, 2017). CK-OSTRec demonstrates how emotion and multilingual metadata can be incorporated to guide recommendations that are culturally contextual and relevant rather than merely popular. However, platform responsibility remains paramount: emotion-aware systems may also generate narrow affective loops (over-recommending a single emotional tone) if diversity is not accounted for. Streaming platforms should therefore balance emotional resonance with exposure diversity to avoid over-personalization and thereby limit the breadth of culture.

6.6 Limitations and Areas for Future Research

Several limitations should be mentioned. Public benchmarks may not capture the complexity of real-world streaming (multi-device listening, evolving preferences, time-of-day/viewing context). Valence-arousal modeling is interpretable, as is emotion perception, but it may be culturally conditioned; future work should incorporate culturally grounded annotations or mixed-methods user research. Metadata-based multilingual modeling supports cross-cultural discovery at the expense of lyric-level cultural semantics; richer depictions of lyrics could be investigated in situations where licensing permits. Finally, future studies should extend the educational dimension through user studies and longitudinal designs to determine the impacts on language curiosity, cultural understanding, and emotional literacy over time.

6.7 Ethical Issues and Responsible Reporting

Although the evaluation is based on non-identifiable, aggregate data, engagement signals can capture personal feelings, emotions, and cultural preferences. Responsible deployment, therefore, requires privacy-preserving data handling and careful communication of system capabilities. Cultural representation should also be handled responsibly to avoid reducing complex cultural expressions to simplistic labels. These considerations make the case for interdisciplinary evaluation frameworks that balance technical validation with social impact evaluation.

Conclusion and Future Work

This study examined whether emotion-aware, multilingual recommendation systems promote cross-cultural engagement with Chinese and Korean OST music on streaming platforms. Using the CK-OSTRec socio-technical framework, we incorporated audio semantics, valence arousal affect modelling, cultural/contextual metadata, and implicit engagement signals to rank OST tracks in multilingual tracks. Across quantitative evaluations, CK-OSTRec improved the quality of top-K ranking relative to representative baselines and was more robust in cold-start settings, with ablation results supporting the added value of the affective and contextual components. Beyond the technical validity of these gains, there are implications for cultural diversity in discovery: algorithmic curation can extend culturally diverse discovery efforts, solidify highly meaningful emotional listening practices, and may support informal learning and emotional literacy through repeated exposure to media. Limitations such as the use of benchmark datasets, limited contextual signals, and culturally biased validation of emotion perception are noted. Future work would include user and longitudinal studies to quantify changes in cultural understanding and learning outcomes, and diversity-aware objectives that balance achieving emotional resonance with exposure to different OST traditions. Building on these findings, future work can further strengthen CK-OSTRec along three practical directions: (i) explainable recommendation features that clarify why a given OST is suggested to support user trust and reflective learning (e.g., interpretable and explainable AI designs) (Fiaz et al., 2025; Abbas et al., 2025; Bilal et al., 2025); (ii) privacy-preserving personalization to reduce risks associated with sensitive listening histories by exploring federated and robustness-aware training strategies (Wang et al., 2023; Jabbar et al., 2025); and (iii) secure deployment considerations for protecting multilingual metadata, user signals, and platform pipelines via layered security and resilient communication approaches (Sajid et al., 2025; Ain et al., 2025). Together, these directions can help move emotion-aware multilingual OST recommendation from offline evaluation toward responsible, user-centered deployment in real streaming ecosystems.

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