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AI-empowered consumer behavior analysis for trustworthy track recommendation over musical dance electronic products

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ABSTRACT

—In the digital music era, accurate and trustworthy track recommendations for musical dance electronic products are becoming increasingly important to improve user experiences and attract more consumers. Consumer behavior modeling is critical in user interest learning and has been extensively used in recommender systems to improve recommendation accuracy. This paper proposes a novel AI-empowered consumer behavior analysis method for trustworthy track recommendations over musical dance electronic products. Specifically, we first model consumer behavior by integrating collaborative filtering and a hidden Markov model to capture the key interactive patterns between consumers and musical dance electronic products. Then, we develop a trustworthy track recommendation method based on multi-layer attention representation learning, which leverages scattering transform for audio preprocessing and attention-based independent recurrent neural networks for encoding user preferences and product features. Extensive experiments on real-world datasets demonstrate the superiority of our proposed method in terms of recommendation accuracy and trustworthiness.

1. Introduction

The rapid advancements in electronic technologies and the digital music industry have led to a proliferation of musical dance electronic products in our daily lives. These products, such as smart speakers, wireless earphones, portable DJ controllers, and LED dance floors, have revolutionized how people experience and interact with music [1–3]. However, the explosive growth of these products has also created a vast and complex landscape, making it challenging for users to discover and select the items that best suit their preferences and needs. To address this issue, there is a pressing need for accurate and trustworthy track recommendation methods specifically tailored for musical dance electronic products. By leveraging advanced AI techniques and user behavior analysis, these methods can help users navigate the massive product space efficiently and effectively, ultimately enhancing their experience and engagement [4–7] (see Table1).

Consumer behavior modeling is one of the pillars upon which recommender systems thrive since it allows businesses to understand customer preferences better [8,9]. By analyzing intricate patterns in customer-item interactions such as clicks (or impressions), purchases, and ratings, consumer behavior modeling extracts valuable insights into customers' decision-making processes, enabling firms to provide more personalized services, thus enhancing consumer satisfaction through increased engagement with their websites [10–12]. Additionally, it comes into play when creating user profiles, which contain detailed representations of an individual's age

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group and lifestyle preferences regarding activities they engage themselves in daily, such as shopping, eating out, or even what they like watching on television [13]. Therefore, by employing consumer behavior modeling, businesses can customize their offerings to meet each client's unique tastes and preferences, thus improving customer satisfaction and revenue generation [14–17]. In today's data-driven business world, consumer behavior modeling is an essential tool with multiple uses.

Many factors in recent years have made trustworthy AI very popular in the academic and industrial sectors [18,19]. AI systems that are increasingly more pervasive and impactful in our daily lives must adhere to a certain code of ethics and values. Trustworthy AI systems observe fundamental properties such as fairness, non-discrimination, transparency, privacy, and security. These properties ensure that AI systems act in manners that are nonpartisan, answerable, and respectful of human rights and dignity [20–22]. Concerning recommendation systems, however, this has shifted towards trustworthy recommendations, which play a major role in building reliable and responsible information services [23]. Furthermore, musical dance electronic products often incorporate sophisticated sensors and controllers that collect and process vast user data [24]. This data could be vulnerable to unauthorized access, manipulation, or misuse if not properly secured. Consequently, there is an urgent need to develop trustworthy track recommendation methods that prioritize user privacy, ensure data security, and provide fair and transparent recommendations. By incorporating robust privacy-preserving techniques, secure data handling protocols, and explainable recommendation algorithms, these methods can foster user trust and mitigate potential risks associated with using musical dance electronic products [25,26].

We focus on musical dance electronic products as our research object due to their growing popularity and unique challenges in recommendation. These products, which include smart speakers, wireless earphones, DJ controllers, and interactive dance floors, combine music playback with movement-based interaction. This creates a complex recommendation problem that must consider audio preferences, physical engagement, and social context. The motivation for this research stems from the rapid growth of the electronic dance music (EDM) industry and the increasing integration of technology into dance experiences. Accurate recommendations in this domain can significantly enhance user engagement, drive product sales, and foster community building around dance music culture.

This study presents a novel approach for analyzing customer behavior using AI. The method focuses on providing trustworthy track recommendations for musical dance electronic devices, aiming to overcome the issues mentioned before. The main contributions can be summarized as follows.

1. We propose a novel consumer behavior modeling approach integrating collaborative filtering (CF) with hidden Markov models (HMM) to capture collaborative signals and sequential patterns in user preferences for musical dance electronic products. This hybrid model allows for a more nuanced understanding of user behavior in the context of dance music consumption and interaction.
2. We develop a trustworthy track recommendation method based on multi-layer attention representation learning. This method leverages scattering transform for robust audio feature extraction and attention-based independent recurrent neural networks to encode user preferences and product features. By incorporating privacy-preserving techniques and explainable AI components, our approach enhances both the accuracy and trustworthiness of recommendations for musical dance electronic products.

The remaining parts of this paper are structured as follows. Section II proposes a consumer behavior modeling method that combines CF and HMM. It also introduces a trustworthy track recommendation method that uses multi-layer attention representation learning. Section III presents the results of the experiment and analysis. Section IV serves as the paper's final section, providing a conclusion.

1.1. *Proposed method*

This section introduces the proposed AI-empowered consumer behavior analysis method for trustworthy track recommendations over musical dance electronic products. We first model consumer behavior by integrating CF and HMM and then develop a trustworthy track recommendation method based on multi-layer attention representation learning.

1.2. *Consumer behavior modeling*

Consumer behavior modeling aims to capture the preferences and interests of consumers from their historical interactions with musical dance electronic products. In the context of trustworthy track recommendation, we propose to model consumer behavior by integrating CF and HMM, which can exploit both the collaborative signals among users and items and the sequential dependencies of

Table 1
Case study on MSD dataset.

Recommendation	Explanation
Song: "Lose Yourself to Dance" by Daft Punk	You may like this song because it has a similar rhythm and melody to the songs you have listened to before, such as "Get Lucky" and "One More Time" by Daft Punk.
Music Video: "Lean On" by Major Lazer & DJ Snake	You may be interested in this music video because it is popular among users with similar preferences as you, and it features a unique blend of electronic dance music and Indian music elements.
Playlist: The Best EDM Songs of 2023	You may enjoy this playlist because it contains several songs that match your favorite genres and artists, such as "Clarity" by Zedd, "Wake Me Up" by Avicii, and "Titanium" by David Guetta.

user preferences, called the CF-HMM model.

Consider $\mathscr{C}$ as the collection of M users and $\mathscr{D}$ as the collection of N musical dance electronic items. The user-product interaction matrix, denoted as $\mathbf{R} \in \mathbb{R}^{M\times N}$, represents the implicit feedback (such as play counts or listening duration) of user c on product d, where r_{cd} is the specific value. The objective of consumer behavior modeling is to develop a preference prediction function $f: \mathscr{C}\times \mathscr{D}\rightarrow \mathbb{R}$ that can estimate the preference score of a customer c for a product d.

To capture the collaborative signals among users and products, we adopt the matrix factorization (MF) technique, which projects users and products into a shared latent space to capture their similarities [27]. Formally, the preference score of user c on product d can be estimated as:

$$\widehat{r}_{cd} = \mathbf{p}_c^\top \mathbf{q}_d \tag{1}$$

where the latent vectors $\mathbf{p}_c$ and $\mathbf{q}_d$ represent the user c and product d in a K-dimensional latent space, respectively. As shown in Eq. (1), the preference score of a user for a product is estimated as the dot product of their respective latent vectors. We optimize the objective function presented in Eq. (2) to learn the latent vectors for users and products.

$$L_{\mathbf{MF}} = \sum_{(c,d)\in\mathscr{O}} \left(r_{cd} - \widehat{r}_{cd}\right)^2 + \lambda\left(|\mathbf{P}|_F^2 + |\mathbf{Q}|_F^2\right) \tag{2}$$

where the set $\mathscr{O}$ represents the observed user-product interactions. The notation $|\cdot|_F$ refers to the Frobenius norm, and λ is the regularization parameter used to avoid overfitting.

However, the MF method only captures the static preferences of users and ignores the dynamic evolution of user interests over time. We further integrate the HMM into the consumer behavior modeling process to model the sequential dependencies of user behaviors. More precisely, we assume that the user's preferences are influenced by their underlying states, and the changes in states follow a first-order Markov chain. Consider the set $\mathscr{S}$, which consists of L latent states denoted as $s_1, s_2, \ldots, s_L$. The probability of transitioning from state s_i to state s_j is denoted by a_{ij}, while the probability of being in the initial state s_i is denoted by π_i. The emission probability of observing product d under state s_l is denoted as $b_l(d)$. Eq. (3) calculates the probability of observing a user behavior sequence $\mathbf{x}_c$ based on the hidden Markov model parameters.

$$P(\mathbf{x}_c|\boldsymbol{\pi}, \mathbf{A}, \mathbf{B}) = \sum_{l_1,l_2,\ldots,l_T} \pi_{l_1} b_{l_1}(x_{c1}) \prod_{t=2}^{T} a_{l_{t-1}l_t} b_{l_t}(x_{ct}) \tag{3}$$

where the vector $\boldsymbol{\pi} = (\pi_1, \pi_2, \ldots, \pi_L)^\top$ represents the initial probabilities of each state. The matrix $\mathbf{A} = (a_{ij})L \times L$ represents the probabilities of transitioning between states. The matrix $\mathbf{B}$ represents the probabilities of emitting certain values from each state. The HMM parameters can be learned by maximizing the log-likelihood of observed user behavior sequences in Eq. (4).

$$L_{\mathbf{HMM}} = \sum_{c=1}^{M} \mathbf{log}\, P(\mathbf{x}_c|\boldsymbol{\pi}, \mathbf{A}, \mathbf{B}) \tag{4}$$

To integrate the CF and HMM components for consumer behavior modeling, we propose a unified CF-HMM model that simultaneously learns the user and product latent vectors and the HMM parameters. As shown in Eq. (5), we assume that the emission probability $b_l(d)$ is proportional to the preference score of product d under state s_l.

$$b_l(d) \propto \widehat{r}_{cd}^{(l)} = \mathbf{p}_c^{(l)\top} \mathbf{q}_d \tag{5}$$

where the latent vector $\mathbf{p}_c^{(l)}$ represents the user c's features in state s_l, and it belongs to the vector space $\mathbb{R}^K$. The unified CF-HMM model is learned by minimizing the objective function presented in Eq. (6).

$$L_{\mathbf{CF-HMM}} = L_{\mathbf{MF}} - \alpha L_{\mathbf{HMM}} + \beta \sum_{l=1}^{L} |\mathbf{P}^{(l)}|_F^2 \tag{6}$$

where the trade-off parameters α and β are used to balance the relative relevance of the CF and HMM components. The matrix $\mathbf{P}^{(l)}$ consists of vectors $\mathbf{p}_1^{(l)}, \mathbf{p}_2^{(l)}, \ldots, \mathbf{p}_M^{(l)}$.

We adopt the alternating optimization strategy to optimize the CF-HMM model, which iteratively updates the user/product latent vectors and HMM parameters. Eq. (7) presents the objective function for updating user and product latent vectors while keeping HMM parameters fixed.

$$L_{\mathbf{CF}} = \sum_{(c,d)\in\mathscr{O}} \left(r_{cd} - \sum_{l=1}^{L} \gamma_c(l) \widehat{r}_{cd}^{(l)}\right)^2 + \lambda\left(|\mathbf{P}|_F^2 + |\mathbf{Q}|F^2\right) + \beta \sum_{l=1}^{L} |\mathbf{P}^{(l)}|_F^2 \tag{7}$$

where the posterior probability $\gamma_c(l)$ represents the likelihood of user c being in state s_l. This probability may be computed using the forward-backward approach. The stochastic gradient descent method can then update the user/product latent vectors.

Then, we fix the user/product latent vectors and update the HMM parameters by maximizing the following objective function in Eq.

(8).

$$L_{\mathbf{HMM}} = \sum_{c=1}^{M} \mathbf{log}\, P(\mathbf{x}_c|\boldsymbol{\pi}, \mathbf{A}, \mathbf{B}) - \alpha \sum_{l=1}^{L} \sum_{d=1}^{N} b_l(v) \mathbf{log}\, b_l(d) \tag{8}$$

where the second term is the entropy regularization to prevent overfitting, the HMM parameters can be updated using the Baum-Welch algorithm [28].

In order to improve the precision and variety of recommendations, we integrate the contextual information of users and items into the CF-HMM model. Let $\mathbf{c}_c$ and $\mathbf{d}_d$ represent the context features of user c and product d, respectively. These features belong to the vector spaces $\mathbb{R}^{D_c}$ and $\mathbb{R}^{D_d}$, where D_c and D_d are the dimensions of the features. As shown in Eq. (9), we assume that the latent vectors of users and products are generated from their context features via linear transformations.

$$\mathbf{p}_c^{(l)} = \mathbf{W}_c^{(l)} \mathbf{c}_c + \mathbf{b}_c^{(l)} \mathbf{q}_c = \mathbf{W}_d \mathbf{d}_d + \mathbf{b}_d \tag{9}$$

where the transformation parameters are denoted as $\mathbf{W}_c^{(l)} \in \mathbb{R}^{K \times D_c}$, $\mathbf{b}_c^{(l)} \in \mathbb{R}^K$, $\mathbf{W}_d \in \mathbb{R}^{K \times D_d}$, and $\mathbf{b}_d \in \mathbb{R}^K$. The objective function of the context-aware CF-HMM model is formulated in Eq. (10).

$$L_{\mathbf{C-CF-HMM}} = L_{\mathbf{CF-HMM}} + \gamma \sum_{l=1}^{L} |\mathbf{W}_c^{(l)}|_F^2 + \eta |\mathbf{W}_d|_F^2 \tag{10}$$

where γ and η are regularization parameters to prevent overfitting.

We further extend the CF-HMM model by incorporating the Markov property into the user latent vectors to capture the local sequential patterns of user behaviors. Eq. (11) defines how the user latent vector at each time step depends on the current state and the previous user latent vector.

$$\mathbf{p}_{ct}^{(l)} = \mathbf{W}p^{(l)} \mathbf{p}_{c,t-1}^{(l)} + \mathbf{W}_c^{(l)} \mathbf{c}_c + \mathbf{b}_c^{(l)} \tag{11}$$

where the matrix $\mathbf{W}_p^{(l)}$ is a transition matrix that represents the transformation of user latent vectors while in state s_l, it has dimensions $K \times K$, and its elements are real numbers. The objective function of the Markov CF-HMM model is presented in Eq. (12).

$$L_{\mathbf{M-CF-HMM}} = L_{\mathbf{C-CF-HMM}} + \mu \sum_{l=1}^{L} \left| \mathbf{W}_p^{(l)} \right|_F^2 \tag{12}$$

where μ is the regularization parameter for the transition matrices.

To capture the nonlinear dependencies between user/product latent vectors and their context features, we can further extend the CF-HMM model by using deep neural networks (DNNs) to learn the latent representations.

$$\mathbf{p}_c^{(l)} = f_c^{(l)}(\mathbf{c}_c) \mathbf{q}_d = f_d(\mathbf{d}_d) \tag{13}$$

where $f_c^{(l)}(\cdot)$ and $f_d(\cdot)$ are DNNs with learnable parameters. Eq. (13) shows how deep neural networks are used to learn the latent representations of users and products. The objective function of the deep CF-HMM model is formulated in Eq. (14).

$$L_{\mathbf{D-CF-HMM}} = L_{\mathbf{CF-HMM}} + \gamma \sum_{l=1}^{L} \left| f_c^{(l)} \right|_2^2 + \eta \left| f_d \right|_2^2 \tag{14}$$

where $|\cdot|_2$ denotes the L2 regularization to prevent overfitting.

For the context-aware CF-HMM, the key features are incorporating the user and item context features, the main assumptions are linear transformations between latent vectors and context features, the objective is capturing the contextual information of users and items, the strengths are improving the recommendation accuracy and diversity, and the weaknesses are increasing the model complexity and data requirement. For the Markov CF-HMM, the key features are incorporating the Markov property into the user latent vectors, the main assumptions are first-order Markov chain of user states, the objective is capturing the local sequential patterns of user behaviors, the strengths are improving the recommendation coherence and smoothness, and the weaknesses are limiting the model flexibility and expressiveness.

To capture the multi-scale sequential patterns of user behaviors, we propose a hierarchical CF-HMM model that learns multiple levels of HMMs to model the user preferences at different granularities. Let $\mathscr{S}^{(1)}, \mathscr{S}^{(2)}, \ldots, \mathscr{S}^{(H)}$ represent H levels of latent state sets. Each set $\mathscr{S}^{(h)}$ consists of L_h states, denoted as $s_1^{(h)}, s_2^{(h)}, \ldots, s_{L_h}^{(h)}$. Assuming that the user behavior sequence is generated by a hierarchical HMM, where the state transitions at level h depend on the states at level $h-1$. The emission probability of observing product d under state $s_l^{(h)}$ at level h is denoted as $b_l^{(h)}(d)$. The probability of transitioning from state $s_i^{(h-1)}$ at level $h-1$ to state $s_j^{(h)}$ at level h is represented by $a_{ij}^{(h)}$. Eq. (15) calculates the probability of observing a user behavior sequence in the hierarchical CF-HMM model.

$$P(\mathbf{x}_c|\mathbf{\Pi},\mathbf{A},\mathbf{B}) = \sum_{l_1^{(1)},\dots,l_T^{(H)}} \prod_{h=1}^{H} \pi^{(h)}_{l_1^{(h)}} \prod_{t=2}^{T} a^{(h)}_{l_{t-1}^{(h-1)},l_t^{(h)}} \prod_{t=1}^{T} b^{(H)}_{l_t^{(H)}}(x_{ct}) \tag{15}$$

where $\mathbf{\Pi} = \boldsymbol{\pi}^{(h)}$ is the set of initial state probability vectors, $\mathbf{A} = \mathbf{A}^{(h)}$ is the set of state transition probability matrices, and $\mathbf{B} = \mathbf{B}^{(h)}$ is the set of emission probability matrices. The objective function of the hierarchical CF-HMM model is presented in Eq. (16).

$$L_{\mathbf{H-CF-HMM}} = L_{\mathbf{CF-HMM}} - \alpha \sum_{u=1}^{M} \log P(\mathbf{x}_c|\mathbf{\Pi},\mathbf{A},\mathbf{B}) + \beta \sum_{h=1}^{H} \sum_{l=1}^{L_h} |\mathbf{P}^{(h,l)}|_F^2 \tag{16}$$

where the matrix $\mathbf{P}^{(h,l)}$ is defined as $\left[\mathbf{p}_1^{(h,l)},\mathbf{p}_2^{(h,l)},\dots,\mathbf{p}_M^{(h,l)}\right]$.

We further extend the hierarchical CF-HMM model by learning personalized transition matrices for each user and product to capture the user-specific and product-specific sequential patterns. Specifically, let $\mathbf{A}_c^{(h)} = \left(a_{c,ij}^{(h)}\right)L_{h-1} \times L_h$ and $\mathbf{A}_d^{(h)} = \left(a_{d,ij}^{(h)}\right)L_{h-1} \times L_h$ be the personalized transition matrices for user c and product d at level h, respectively. As shown in Eq. (17), the transition probabilities are parameterized using personalized latent vectors for users and products.

$$a_{c,ij}^{(h)} = \frac{\exp\left(\mathbf{w}_{c,i}^{(h-1)\top}\mathbf{w}_{c,j}^{(h)}\right)}{\sum_{j'=1}^{L_h}\exp\left(\mathbf{w}_{c,i}^{(h-1)\top}\mathbf{w}_{c,j'}^{(h)}\right)} a_{d,ij}^{(h)} = \frac{\exp\left(\mathbf{w}_{d,i}^{(h-1)\top}\mathbf{w}_{d,j}^{(h)}\right)}{\sum_{j'=1}^{L_h}\exp\left(\mathbf{w}_{d,i}^{(h-1)\top}\mathbf{w}_{d,j'}^{(h)}\right)} \tag{17}$$

where the personalized latent vectors for user c and product d under state $s_i^{(h)}$ at level h are denoted as $\mathbf{w}_{c,i}^{(h)} \in \mathbb{R}^K$ and $\mathbf{w}_{d,i}^{(h)} \in \mathbb{R}^K$, respectively. The objective function of the personalized hierarchical CF-HMM model is formulated in Eq. (18).

$$L_{\mathbf{PH-CF-HMM}} = L_{\mathbf{H-CF-HMM}} + \gamma \sum_{c=1}^{M} \sum_{h=1}^{H} \sum_{l=1}^{L_h} \left|\mathbf{w}_{c,l}^{(h)}\right|_2^2 + \eta \sum_{d=1}^{N} \sum_{h=1}^{H} \sum_{l=1}^{L_h} \left|\mathbf{w}_{d,l}^{(h)}\right|_2^2 \tag{18}$$

where γ and η are regularization parameters for user and product personalized latent vectors.

To incorporate the social relationships among users into the hierarchical CF-HMM model, we assume that their social neighbors influence the user latent vectors. Consider the user social matrix $\mathbf{S}$, a square matrix of size $M \times M$ where each element $s_{cc'}$ represents the social connection between users c. Eq. (19) defines the social regularization term, which encourages socially connected users to have similar latent vectors.

$$L_{\mathbf{social}} = \frac{1}{2} \sum_{c=1}^{M} \sum_{c'=1}^{M} s_{cc'} \sum_{h=1}^{H} \sum_{l=1}^{L_h} |\mathbf{p}_c^{(h,l)} - \mathbf{p}_{c'}^{(h,l)}|_2^2 \tag{19}$$

which encourages socially connected users to have similar latent vectors. The objective function of the social hierarchical CF-HMM model is presented in Eq. (20).

$$L_{\mathbf{SH-CF-HMM}} = L_{\mathbf{H-CF-HMM}} + \lambda L_{\mathbf{social}} \tag{20}$$

where λ is the trade-off parameter.

We enhance the hierarchical CF-HMM model by acquiring knowledge from numerous user latent matrices for each state. As shown in Eq. (21), the emission probability of observing product d is defined using multiple user latent matrices for each state $s_l^{(h)}$.

$$b_l^{(h)}(d) \propto \sum_{k=1}^{K} \theta_{lk}^{(h)} \exp\left(\mathbf{p}_{k,c}^{(h,l)\top}\mathbf{q}_d\right) \tag{21}$$

where $\theta_{lk}^{(h)}$ is the weight of the k-th latent matrix under state $s_l^{(h)}$ at level h, and $\sum_{k=1}^{K}\theta_{lk}^{(h)} = 1$. The objective function of the diverse hierarchical CF-HMM model is formulated in Eq. (22).

$$L_{\mathbf{DH-CF-HMM}} = L_{\mathbf{H-CF-HMM}} + \beta \sum_{h=1}^{H} \sum_{l=1}^{L_h} \sum_{k=1}^{K} \left|\mathbf{P}_k^{(h,l)}\right| F^2 + \rho \sum_{h=1}^{H} \sum_{l=1}^{L_h} \sum_{k=1}^{K} \theta_{lk}^{(h)} \log \theta_{lk}^{(h)} \tag{22}$$

where ρ is the regularization parameter for the weight distribution.

Ultimately, we integrate the item co-occurrence patterns into the hierarchical CF-HMM model to address the sparse data problem and improve the variety of recommendations. Consider $\mathbf{C}$ as the item co-occurrence matrix, with dimensions $\mathbb{R}^{N\times N}$. Here, $c_{dd'}$ represents the frequency of co-occurrence of items d and d' in user behavior sequences. Eq. (23) defines the item co-occurrence regularization term, which encourages co-occurring products to have similar latent vectors.

$$L_{\mathbf{co-occur}} = -\frac{1}{2}\sum_{d=1}^{N}\sum_{d'=1}^{N} c_{dd'} \left| \mathbf{q}_d - \mathbf{q}_{d'} \right|_2^2 \tag{23}$$

which encourages co-occurring products to have similar latent vectors. The objective function of the co-occurrence-aware hierarchical CF-HMM model is presented in Eq. (24).

$$L_{\mathbf{CH-CF-HMM}} = L_{\mathbf{H-CF-HMM}} + \xi L_{\mathbf{co-occur}} \tag{24}$$

where ξ is the trade-off parameter for the item co-occurrence regularization term.

The CF-HMM model integrates the matrix factorization and hidden Markov model to capture both the collaborative signals and sequential patterns of user preferences.

1.3. Trustworthy track recommendation

Based on the consumer behavior model, we develop a trustworthy track recommendation method to provide reliable and secure electronic product recommendations for musical dance. Our method adopts a multi-layer attention representation learning framework to encode user preferences and product features, which can effectively capture the importance of different user-product interactions and sequential patterns.

Specifically, we first employ the scattering transform to preprocess the audio signals of user listening history, which can extract multi-scale features and recover the information loss in traditional MFCC [29]. We use two scattering transform layers to extract multi-scale and informative features from the audio signals of musical dance electronic products. The first layer uses a low-pass filter and a set of wavelets with eight scales and eight orientations. The second layer uses the same wavelets with four scales and eight orientations. The output of the scattering transform is a set of scattering coefficients. Let c be the user's listening sequence. Eq. (25) defines the scattering transform of the audio features $\mathbf{x}_{ct}$, which extracts multi-scale and informative features from the audio signals.

$$\mathbf{S}_x(\mathbf{x}_{ct}, \lambda_1, \lambda_2) = ||\mathbf{x}_{ut} * \psi_{\lambda_1}| * \psi_{\lambda_2}| * \phi \tag{25}$$

where $*$ denotes the convolution operator, ϕ is a low-pass filter, ψ_{λ_1} and ψ_{λ_2} are the first-order and second-order wavelet filters at scales λ_1 and λ_2, respectively.

Next, we develop a new attention-based independent recurrent neural network (AIRNN) to acquire the user preference representation from the scattering coefficients. The AIRNN model comprises many IRNN layers, including residual connections and attention processes. The general structure of our suggested approach is shown in Fig. 1.

Fig. 1 illustrates the architecture of the proposed secure and trustworthy AI-powered recommendation for musical dance electronic

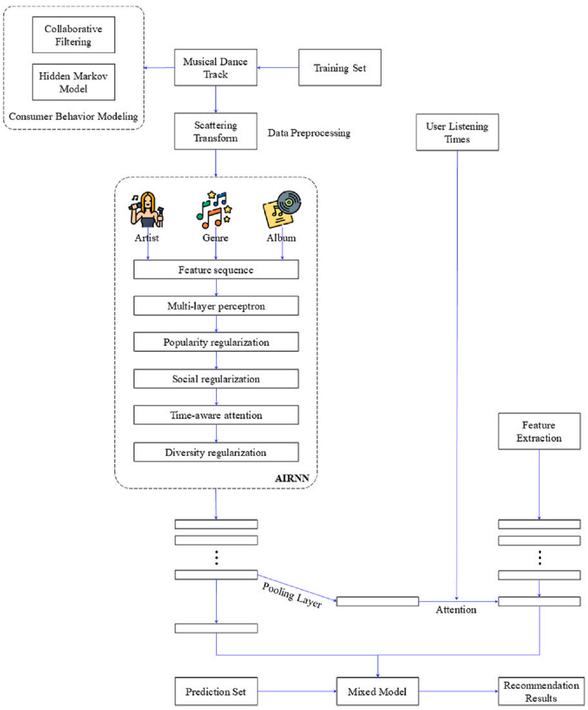


Fig. 1. Overall architecture.

products method. The process begins with data preprocessing, where user listening history and product metadata are collected and cleaned. The scattering transform is then applied to extract multi-scale audio features from the preprocessed data.

The consumer behavior modeling component integrates collaborative filtering and hidden Markov models to capture user-item interactions and sequential patterns. This hybrid model feeds into the core recommendation engine, which utilizes an AIRNN for feature extraction and representation learning.

The multi-layer perceptron (MLP) component combines user preferences, product features, and contextual information to generate initial recommendations. These recommendations are then refined through additional modules.

- The popularity regularization module helps balance between popular and niche items.
- Social regularization incorporates user social network data to enhance recommendations.
- The feature sequence module captures temporal dynamics in user preferences.

Finally, the system outputs personalized and trustworthy recommendations for musical dance electronic products and explanations for each recommendation to enhance user trust and system transparency.

Let $\mathbf{h}_t^l \in \mathbb{R}^{D_h}$ represent the hidden state of the l-th IRNN layer at time step t, with D_h denoting the hidden dimension. As shown in Eq. (26), the hidden state of each IRNN layer is updated based on the previous hidden state and the current input.

$$\mathbf{h}_t^l = \sigma\left(\mathbf{W}_h^l \mathbf{S}_x(\mathbf{x}_{ct}, \lambda_1, \lambda_2) + \mathbf{u}^l \odot \mathbf{h}_{t-1}^l + \mathbf{b}_h^l\right) \tag{26}$$

where the weight matrix $\mathbf{W}_h^l$ is a $D_h \times D_s$ matrix, and the bias vector $\mathbf{b}_h^l$ is a D_h vector for the l-th layer. The recurrent weight vector $\mathbf{c}^l$ is a D_h vector. The symbol $\odot$ represents element-wise multiplication, and σ denotes the activation function. Compared with the traditional RNN, the IRNN can effectively capture the long-term dependencies and avoid the gradient vanishing and exploding problems [30].

Moreover, we introduce an attention mechanism to select the important hidden states for user preference modeling adaptively. Eq. (27) calculates the attention weight α_t^l of the l-th layer at time step t for each hidden state in the AIRNN model.

$$\alpha_t^l = \frac{\exp\left(\mathbf{v}_\alpha^{l\top} \ \mathbf{tanh}\left(\mathbf{W}\alpha^l \mathbf{h}_t^l + \mathbf{b}\alpha^l\right)\right)}{\sum_{\tau=1}^{T} \exp\left(\mathbf{v}_\alpha^{l\top} \ \mathbf{tanh}\left(\mathbf{W}\alpha^l \mathbf{h}_\tau^l + \mathbf{b}\alpha^l\right)\right)} \tag{27}$$

where the learnable parameters are represented as $\mathbf{W}\alpha^l \in \mathbb{R}^{D_a \times D_h}$, $\mathbf{b}\alpha^l \in \mathbb{R}^{D_a}$, and $\mathbf{d}_\alpha^l \in \mathbb{R}^{D_a}$. Here, D_a refers to the attention dimension. The attended hidden state $\widehat{\mathbf{h}}_t^l$ is obtained through Eq. (28), which applies the attention weights to the hidden states.

$$\widehat{\mathbf{h}}_t^l = \alpha_t^l \mathbf{h}_t^l \tag{28}$$

As shown in Eq. (29), the final user preference representation $\mathbf{z}_c$ is obtained by concatenating the attended hidden states of all layers.

$$\mathbf{z}_c = \left[\widehat{\mathbf{h}}_T^1; \widehat{\mathbf{h}}_T^2; \ldots; \widehat{\mathbf{h}}_T^L\right] \tag{29}$$

where L is the number of IRNN layers.

We can learn the product feature representation $\mathbf{e}_d$ using the AIRNN model from the audio content and metadata (e.g., artist, genre, album) of each musical dance electronic product d. Eq. (30) defines how the product feature representation $\mathbf{e}_d$ is learned using the AIRNN model.

$$\mathbf{g}_{t'}^l = \sigma\left(\mathbf{W}_g^l \mathbf{y}_{dt'} + \mathbf{v}^l \odot \mathbf{g}t' - 1^l + \mathbf{b}_g^l\right)$$

$$\beta_{t'}^l = \frac{\exp\left(\mathbf{v}\beta^{l\top} \ \mathbf{tanh}\left(\mathbf{W}\beta^l \mathbf{g}_{t'}^l + \mathbf{b}\beta^l\right)\right)}{\sum_{\tau'=1}^{T'} \exp\left(\mathbf{v}\beta^{l\top} \ \mathbf{tanh}\left(\mathbf{W}\beta^l \mathbf{g}_{\tau'}^l + \mathbf{b}\beta^l\right)\right)}$$

$$\widehat{\mathbf{g}}_{t'}^l = \beta_{t'}^l \mathbf{g}_{t'}^l$$

$$\mathbf{e}_d = \left[\widehat{\mathbf{g}}_{T'}^1; \widehat{\mathbf{g}}_{T'}^2; \ldots; \widehat{\mathbf{g}}_{T'}^L\right] \tag{30}$$

where the learnable parameters of the product feature encoder are denoted as $\mathbf{W}_g^l$, $\mathbf{b}_g^l$, $\mathbf{d}^l$, $\mathbf{W}\beta^l$, $\mathbf{b}\beta^l$, and $\mathbf{d}_\beta^l$.

In order to account for the complex relationships between user preferences and product attributes, we propose using a MLP to train the interaction function effectively. The interaction score between a user and a product is calculated using the MLP as shown in Eq. (31).

$$\mathbf{m}_0 = [\mathbf{z}_c; \mathbf{e}_d]$$

$$\mathbf{m}_i = \sigma(\mathbf{W}_i \mathbf{m}_{i-1} + \mathbf{b}i), i = 1, 2, \ldots, I-1$$
$$\widehat{r}_{cd} = \mathbf{w}_I^\top \mathbf{m}_{I-1} + b_I \tag{31}$$

where the learnable parameters of the MLP are denoted as $\mathbf{W}_i$, $\mathbf{b}_i$, $\mathbf{w}_I$, and b_I. The variable I represents the number of layers, while σ represents the activation function.

We incorporate a popularity regularization term into the objective function to enhance the recommendation diversity and alleviate the popularity bias. Let p_d represent the popularity score of product d. This score is determined by dividing the number of interactions on product d by the total number of interactions. Eq. (32) defines the popularity regularization term, which encourages the recommendation of less popular products.

$$L_{\mathbf{pop}} = \frac{1}{2} \sum_{(c,d) \in \mathcal{O}} (p_d - \overline{p})^2 \tag{32}$$

where $\mathcal{O}$ is the set of observed user-product interactions, and $\overline{p}$ is the average popularity score of all products. By minimizing $L_{\mathbf{pop}}$, the model is encouraged to recommend less popular products and improve the recommendation diversity.

To incorporate the social relationships among users into the recommendation model, we introduce a social regularization term to constrain the user preference representations. Let $\mathbf{S} \in \mathbb{R}^{M \times M}$ represent the user social matrix. In this matrix, the entry $s_{cc'}$ equals 1 if users c and c' are socially related, and 0 otherwise. The social regularization term is defined in Eq. (33), which encourages socially connected users to have similar preference representations.

$$L_{\mathbf{social}} = \frac{1}{2} \sum_{c=1}^{M} \sum_{c'=1}^{M} s_{cc'} \left| \mathbf{z}_c - \mathbf{z}_{c'} \right|_2^2 \tag{33}$$

By minimizing $L_{\mathbf{social}}$, the model encourages socially connected users to have similar preference representations and enhances the recommendation quality.

We incorporate the time information into the recommendation model to capture the temporal dynamics of user preferences. Specifically, let t_{cd} be the timestamp of the interaction between user c and product d. We include a time-aware attention method to acquire the temporal weights of various interactions. Eq. (34) calculates the temporal weight γ_{cd} of each interaction (c, d) using a time-aware attention method.

$$\gamma_{cd} = \frac{\exp\left(\mathbf{v}_\gamma^\top \tanh\left(\mathbf{W}_\gamma [\mathbf{z}_c; \mathbf{e}_d; \mathbf{t}_{cd}] + \mathbf{b}_\gamma\right)\right)}{\sum_{(c',d') \in \mathcal{O}_c} \exp\left(\mathbf{v}_\gamma^\top \tanh\left(\mathbf{W}_\gamma [\mathbf{z}_{c'}; \mathbf{e}_{d'}; \mathbf{t}_{c'd'}] + \mathbf{b}_\gamma\right)\right)} \tag{34}$$

where the learnable parameters in this context are represented by $\mathbf{W}_\gamma$, $\mathbf{b}_\gamma$, and $\mathbf{d}_\gamma$. The time embedding vector is denoted as $\mathbf{t}_{cd} \in \mathbb{R}^{D_t}$, where D_t represents the dimension of the time embedding. Additionally, $\mathcal{O}_c$ refers to the set of interactions of user c. The time-aware interaction score $\widetilde{r}_{cd}$ is obtained through Eq. (35), which incorporates the temporal weights.

$$\widetilde{r}_{cd} = \gamma_{cd} \widehat{r}_{cd} \tag{35}$$

The final objective function for learning the model parameters is presented in Eq. (36).

$$\begin{aligned} L = & \sum_{(c,d) \in \mathcal{O}} \ln \sigma(\widetilde{r}_{cd}) \\ & + \sum_{(c,d') \in \mathcal{O}_c^-} \ln(1 - \sigma(\widetilde{r}_{cd'})) + \lambda_1 L_{\mathbf{pop}} + \lambda_2 L_{\mathbf{social}} + \lambda_3 \left| \mathbf{\Theta} \right|_2^2 \end{aligned} \tag{36}$$

where the set of negative samples for user c, denoted as $\mathcal{O}_c^-$, is randomly selected from the unobserved products. The sigmoid function is represented by σ. Θ represents the set of all learnable parameters, while λ_1, λ_2, and λ_3 are the regularization coefficients.

2. Experiments and results analysis

This study proposes a secure and trustworthy AI-powered recommendation for musical dance electronic products, short for the STAR-MDE method. In this part, we execute comprehensive tests to assess the effectiveness of our proposed STAR-MDE technique for reliable track recommendation in electronic devices for musical dance. We provide an overview of the experimental configuration and offer the findings and a thorough examination.

3. Experimental setup

We evaluate our method on two real-world datasets: MSD and Spotify. The MSD dataset contains the listening history of 571,355 users on 41,785 musical dance electronic products, including songs, music videos, and playlists, from the Last.fm platform. The data spans from January 2015 to December 2022. The Spotify dataset contains 1,021,961 users, 174,389 products, and their interactions, such as streams, follows, and shares, from the Spotify music platform. The data covers the period from July 2017 to June 2023. We use a random selection process for every dataset to allocate 80 % of the user-product interactions for training, 10 % for validation, and 10 % for testing.

We evaluate our approach by comparing it to five contemporary and very advanced music recommendation methods.

- Music-CRN [31]: A straightforward and efficient model that aids in categorizing and recommending music by learning the auditory content aspects of the song.
- MMusic [32]: A hierarchical multi-information fusion technique is proposed for deep music recommendation. This method effectively utilizes the characteristics of different types of information and enhances the learning of user and music representations.
- MEGAN [33]: A novel approach called multi-view enhanced graph attention network is proposed for session-based music recommendation.
- ATPP [34]: A new method for sequential music recommendation. It consists of a temporal point process model and an attention mechanism.
- HEMR [35]: A hypergraph embedding framework for music recommendation based on hypergraph embedding.

Each baseline addresses different aspects of the challenge. Music-CRN focuses on audio content analysis, which is crucial for understanding musical features. MMusic utilizes multi-information fusion, similar to our approach of integrating multiple data sources. MEGAN employs graph attention networks for session-based recommendations, capturing complex user-item interactions. ATPP incorporates temporal dynamics, which is important for modeling evolving user preferences in dance music. HEMR uses hypergraph embedding, offering a different perspective on modeling complex relationships in music data.

In order to evaluate the effectiveness of the recommendation, we use three commonly employed metrics: hit ratio at rank K (HR@K), normalized discounted cumulative gain at rank K (NDCG@K), and recommended musical dance electronic products accuracy rate (RMAR). HR@K measures the percentage of users whose top-K recommended products contain at least one product they interacted with in the test set. NDCG@K measures the normalized discounted cumulative gain of the top-K recommended products, which considers the position and relevance of the products. RMAR measures the accuracy of the recommended products compared to the user's interacted products in the test set. The hit ratio at rank K (HR@K) is calculated using Eq. (37), while the normalized discounted cumulative gain at rank K (NDCG@K) is computed using Eq. (38).

$$\mathbf{HR@K} = \frac{1}{|\mathscr{C}|}\left(R_c \cap S_c^K \neq \varnothing\right) \tag{37}$$

$$\mathbf{NDCG@K} = \frac{1}{|\mathscr{C}|}\sum_{c\in\mathscr{C}} \frac{\mathbf{DCG@K}\left(S_c^K\right)}{\mathbf{IDCG@K}\left(S_c^K\right)} \tag{38}$$

where $\mathscr{C}$ represent the set of users, R_c represent the set of products that user c has interacted with in the test set, S_c^K represent the set of top-K recommended products for user c, and $\mathbf{DCG@K}\left(\mathbf{S_c^K}\right)$ and $\mathbf{IDCG@K}\left(\mathbf{S_c^K}\right)$ represent the discounted cumulative gain and ideal discounted cumulative gain at rank K for user c, respectively.

The RMAR is defined in Equation (39).

$$\mathbf{RMAR} = \frac{1}{|\mathscr{C}|}\sum_{c\in\mathscr{C}} \frac{|\widehat{R}_c \cap R_c|}{|\widehat{R}_c|} \tag{39}$$

where $\widehat{R}_c$ represents the suggested items for user c, and R_c represents the products that user c has interacted with in the test set.

To evaluate the trustworthiness of the recommendation, we design two metrics: Privacy Score and Security Score. Privacy Score measures the percentage of private attributes that cannot be inferred from the recommended products, while Security Score measures the percentage of sensitive information that cannot be deduced from the recommended products. The privacy score, which measures the protection of private attributes, is calculated using Eq. (40).

$$\textbf{Privacy Score} = 1 - \frac{1}{|\mathscr{C}|}\sum_{c\in\mathscr{C}} \frac{|\widehat{P}_c \cap P_c|}{|\widehat{P}_c|} \tag{40}$$

where $\widehat{P}_c$ is the set of private attributes (e.g., gender, age, location) that can be inferred from the recommended products for user c, and P_c is the set of true private attributes of user c. A higher Privacy Score indicates better privacy protection.

The security score, which assesses the protection of sensitive information, is computed using Eq. (41).

$$\textbf{Security Score} = 1 - \frac{1}{|\mathscr{C}|}\sum_{c\in\mathscr{C}} \frac{|\widehat{S}_c \cap S_c|}{|\widehat{S}_c|} \tag{41}$$

where $\widehat{S}_c$ represents the set of sensitive information, such as credit card numbers or social security numbers, that can be deduced from the suggested goods for user c. S_c represents the actual set of sensitive information belonging to user c. A higher Security Score indicates a better security guarantee.

Our STAR-MDE method uses two scattering transform layers and 3 AIRNN layers. The hidden dimension of AIRNN is set to 128, while the attention dimension is set to 64. The learning rate is set to 0.001, and the batch size is set to 256. We apply L2 regularization with a coefficient of 0.0001 to prevent overfitting. The privacy budget, denoted as ϵ, is set to 1.0. Finally, we use three shares in MPC. The hyperparameters of baselines are tuned to achieve their best performance.

The parameters in our STAR-MDE method were tuned through a combination of grid search and empirical optimization on the validation set. We used two scattering transform layers and 3 AIRNN layers, as this configuration provided the best balance between feature richness and model complexity. The hidden dimension of AIRNN was set to 128, while the attention dimension was set to 64, offering sufficient representational capacity without overfitting. We employed the Adam optimizer with a learning rate of 0.001 and a batch size 256, providing stable and efficient training. L2 regularization with a coefficient of 0.001 was applied to prevent overfitting. The privacy budget ϵ was set to 1.0, balancing privacy protection and utility based on common practices in differential privacy literature. These parameters were then applied to the test set for final evaluation.

4. Performance comparison

Fig. 2 illustrates the proposed STAR-MDE approach's recommendation performance and the MSD dataset's baselines. The proposed STAR-MDE method employs the scattering transform to extract multi-scale and informative features from the musical dance electronic products, which can capture the complex and dynamic patterns of audio signals.

Fig. 3 shows the recommendation performance of our STAR-MDE method and the baselines on the Spotify dataset. Again, the proposed method demonstrates superior performance across all criteria. Our technique significantly improves HR@10, NDCG@10, and RMAR compared to the best baseline HEMR. The findings illustrate the resilience and applicability of our approach across various datasets and platforms. Furthermore, the disparities in performance between our approach and the reference models are less pronounced while analyzing the Spotify dataset compared to the MSD dataset.

Fig. 4 displays the performance of our STAR-MDE approach and the baselines on the two datasets regarding trustworthiness. Our technique demonstrates superior performance in terms of both Privacy Score and Security Score compared to all other methods. The findings unequivocally illustrate the efficacy of our approach in safeguarding user privacy and fortifying recommendation security.

In order to evaluate the efficacy of various elements in our STAR-MDE approach, we conducted an ablation study by systematically eliminating each component from the whole model and assessing its performance on the MSD dataset. Fig. 5 displays the outcomes of the ablation trial. It is evident that the removal of any component will result in a decrease in performance, highlighting the importance and contribution of each component. Notably, the largest performance drop occurs when the scattering transform module is removed, followed by the removal of the attention mechanism, differential privacy, secure multi-party computation, blockchain, data cleaning, and augmentation, multi-modal and multi-task learning, and an explainable and interactive interface.

We also investigate the sensitivity of our STAR-MDE method to different hyperparameters, including the number of scattering transform layers, the number of AIRNN layers, the hidden dimension of AIRNN, and the attention dimension. Fig. 6 illustrates the performance of our STAR-MDE method under various hyperparameter configurations on the MSD dataset. Our approach exhibits notable robustness across a reasonable range of hyperparameter values, indicating its stability and adaptability. Particularly, we observe that increasing the number of AIRNN layers from 1 to 4 leads to a significant performance boost, likely due to the model's enhanced ability to capture complex patterns in the data. However, further increases beyond four layers result in performance degradation, which can be attributed to the increased difficulty in training deeper models and potential overfitting issues. Our analysis reveals optimal performance when setting the hidden dimension to 128 and the attention dimension to 64. These findings highlight the

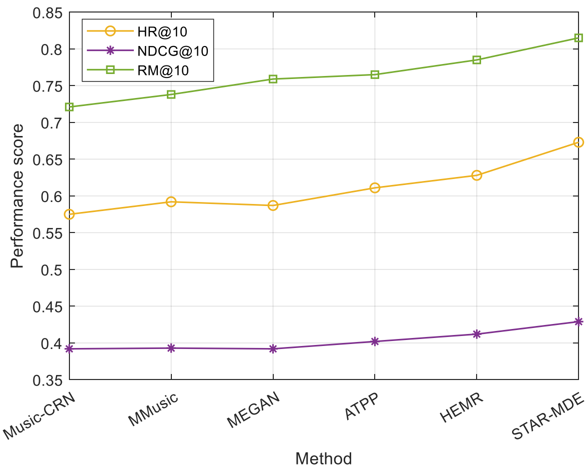


Fig. 2. Recommendation performance on MSD dataset.

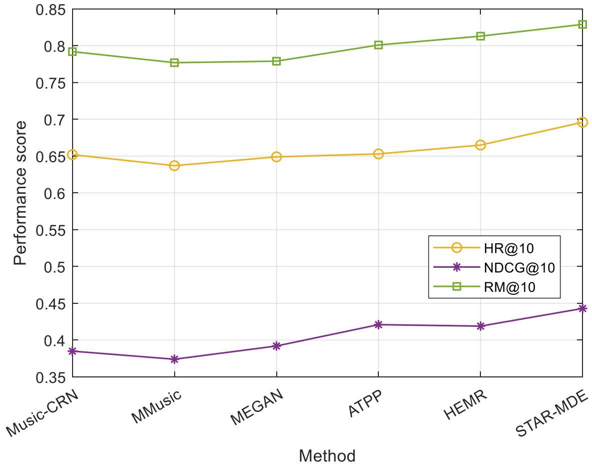
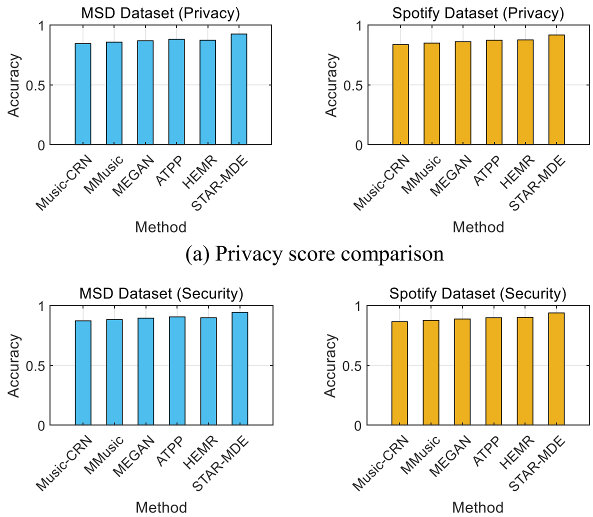


Fig. 3. Recommendation performance on Spotify dataset.



(a) Privacy score comparison

(b) Security score comparison

Fig. 4. Trustworthiness performance on two datasets.

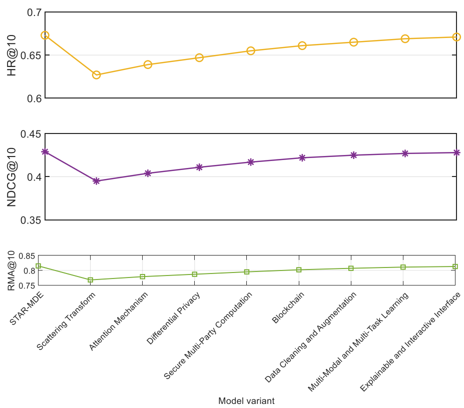


Fig. 5. Ablation study on MSD dataset.

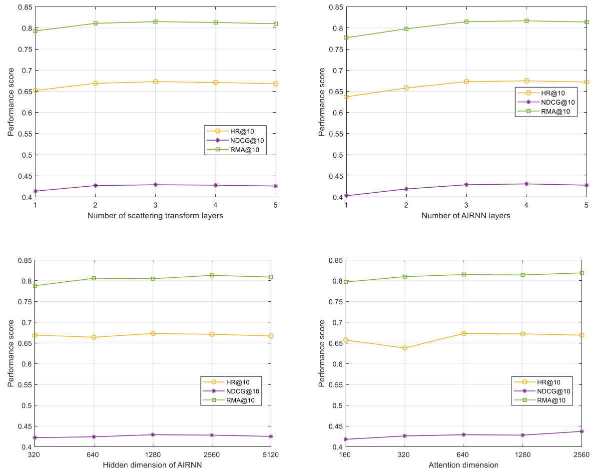


Fig. 6. Hyperparameter sensitivity analysis on MSD dataset.

importance of careful hyperparameter tuning in maximizing our STAR-MDE method's effectiveness while showcasing its inherent stability across a wide range of configurations, which is crucial for practical applications in diverse recommendation scenarios.

In order to provide more evidence of the efficacy and comprehensibility of our STAR-MDE technique, we conduct a case study on the MSD dataset. Table 1 shows the results of our method's recommendation and explanations for a sample user. Our method can recommend diverse and relevant musical dance electronic products to the user, such as songs, music videos, and playlists. Moreover, our method can provide persuasive explanations for each recommendation, such as "You may like this song because it has a similar rhythm and melody to the songs you have listened to before," "You may be interested in this music video because it is popular among users with similar preferences as you," and "You may enjoy this playlist because it contains several songs that match your favorite genres and artists." The explanations help the user understand the reasons behind the recommendations and make informed decisions. The case study demonstrates the potential of our method in providing personalized and trustworthy recommendations for musical dance electronic products.

In summary, the experimental findings clearly show that our STAR-MDE technique outperforms other methods regarding recommendation accuracy, privacy protection, security improvement, robustness, and interpretability. The ablation study, hyperparameter sensitivity analysis, and case study provide in-depth insights into the effectiveness and necessity of each component in our method. The qualitative and quantitative analyses shed light on the potential of our method in providing trustworthy and personalized recommendations for musical dance electronic products.

5. Conclusion

This paper proposed a novel, secure, and trustworthy AI-powered recommendation method for musical dance electronic products. We performed extensive experiments on two datasets to assess our approach's efficacy. The performance of our technique surpasses that of the most advanced baselines in terms of suggestion accuracy, privacy protection, and security assurance. Moreover, we demonstrated the effectiveness and necessity of each component in our method through ablation study, hyperparameter sensitivity analysis, and case study. Our work sheds light on developing trustworthy and secure recommendation systems for electronic musical dance products, and it has the potential to benefit both users and businesses in the music industry. One limitation of our work is that we only focus on the audio content and metadata of electronic musical dance products.

In future work, we plan to expand our research in several directions. We will explore multi-modal data integration, incorporating user-generated content, visual information from music videos, and physiological data from wearable devices to provide a richer context for understanding user preferences and dance behaviors. Advanced temporal modeling techniques like transformers or temporal graph neural networks will be investigated to capture better long-term dependencies and seasonal patterns in dance music preferences. We aim to enhance contextual and situational awareness by incorporating real-time factors like time of day, weather, and social settings to provide more adaptive recommendations. To further improve privacy protection, we will explore federated learning techniques that allow model training across decentralized edge devices without sharing raw user data. We also plan to develop more advanced explainable AI techniques tailored for music and dance recommendations, potentially incorporating domain knowledge from musicology and dance studies. Additionally, we will investigate cross-domain applications of our STAR-MDE method to areas involving content consumption and physical interaction, such as video games or virtual reality experiences. Finally, we intend to conduct extensive user studies and pilot deployments in real-world settings like dance clubs and fitness centers to gather qualitative feedback and assess the practical impact of our recommendation system on user experience and engagement in dance music contexts.

Data availability statement

Data will be made available on request.

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CRediT authorship contribution statement

Fenglei Wang: Writing – original draft, Methodology, Investigation, Conceptualization. **Adam Slowik:** Writing – review & editing, Software, Resources, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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