HUMMUS: A Human-Centered Approach to Sequential Recommendation Explainability through Data Humanism

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Abstract

Sequential music recommendation systems operate as "black boxes," reducing user agency and failing to support collaborative decision-making in group settings. To address these limitations, we present HUMMUS, an interactive group recommender system that applies Data Humanism principles. HUMMUS visualizes songs as flowers where petals represent audio features, connecting lines reveal algorithmic relationships, and real-time voting enables collaborative playlist creation between users and algorithms. Through a mixed-methods evaluation with 19 participants across collaborative playlist creation scenarios, we demonstrate that this humanistic approach appears to enhance user understanding of recommendations, collaborative engagement, and satisfaction. Participants reported positive emotional responses while maintaining recommendation quality. Our contributions include: a flower-based visualization technique for interpretable audio features, a real-time collaborative voting framework, and evidence that artistic metaphors enhance algorithmic transparency without sacrificing functionality. This research establishes Data Humanism as a viable framework for human-centered recommender systems that prioritize understanding and collaborative discovery alongside algorithmic sophistication.

Keywords

sequential music recommendation, human-centered recommender systems, explainable AI, data humanism, user interface design, user experience design

1. Introduction

Sequential Recommender Systems (SRS) are widely deployed in major music streaming platforms and have significantly influenced music discovery patterns [1, 2, 3, 4]. However, these systems operate as "black boxes", limiting user agency and encourage passive consumption [5, 6]. This opacity becomes particularly problematic in collaborative music settings, e.g., parties, co-sharing commuting, or workspaces, where music serves as a medium for connection and shared experience [7, 8]. To increase transparency, traditional approaches to explainable recommendation mainly focus on technical transparency through post-hoc explanations, failing to address the relational, contextual, and emotional dimensions of collaborative music experience [9, 10].

SRS present unique challenges, including recommendations that must account for temporal context, mood evolution, and remain interpretable to users without technical expertise [11, 12]. Moreover, when these systems are embedded in collaborative settings, such as the co-creation of music playlists, properly modeling the group dynamics is also a key factor. Typically, existing systems optimize for individual preferences or treat group recommendation as an aggregation problem, missing opportunities for collaborative sense-making and serendipitous discovery between the various users but also between users and algorithm [13, 14].

How can Data Humanism inform the design of explainable sequential music recommender systems to enhance both transparency and collaborative engagement?

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We address this research question by presenting HUMMUS, an interactive music SRS designed by following Data Humanism principles, like *small data*, *embracing imperfection* and *subjectivity*, prioritizing human connection over algorithmic optimization, and aligning with the social nature of music consumption.

Our contributions include: (1) a novel application of Data Humanism to music SRS, (2) design patterns for real-time collaborative music recommendation interfaces, and (3) evidence that artistic metaphors can enhance algorithmic transparency without sacrificing functionality.

2. Related Work

2.1. Music Recommendation

Sequential Recommendations – SRS represent an evolution in personalized music discovery, leveraging the temporal nature of music consumption to predict user preferences [1]. Advancement happen through deep learning architectures, like Transformer models [15], RNNs/LSTMs [16, 17], and specialized session-based approaches [18, 19]. Transformer-based architectures like BERT4Rec [15] and SASRec [20] employ self-attention mechanisms to model sequential dependencies in listening behaviors. Recurrent neural networks that capture temporal patterns in music playlists and listening sessions [16]. While, session-based model short-term user interactions within listening sessions [18]. These approaches address unique challenges in the music domain including the prevalence of repeat listening, the importance of sequential context, and the need for real-time recommendations during active listening sessions [1]. However, despite these algorithmic advances, SRS in the music domain remain largely opaque to end users, who cannot understand how their listening history influences future recommendations or have an active role steering the sequence [2].
Group Recommendations and Collaborative Playlist Creation – Group recommendation approaches in music settings leverage social choice theory and consensus mechanisms, employing methods that range from traditional aggregation strategies to neural architectures [21, 22]. Recent work emphasizes multi-stakeholder fairness, addressing bias concerns across users, artists, and platforms while handling conflicting musical tastes within groups [23].

Collaborative playlist creation evolved beyond simple shared editing to incorporate social dynamics, cross-cultural considerations, and real-time synchronization features [24, 25]. User studies reveal that successful collaborative playlists depend on clear communication protocols, balanced contribution mechanisms, and culturally-sensitive design choices that accommodate varying collaboration styles across different regions [26, 25]. Nevertheless, these systems face unique challenges in music recommendation, including the need to balance individual agency with group consensus, manage social dynamics during playlist creation, and provide transparent explanations for group-level recommendations that satisfy diverse stakeholders.

2.2. Human-centered and Explainable Recommender Systems

Human-centered and explainable recommender systems represent a shift in recommendation research, moving beyond accuracy-focused algorithmic improvements to address the complex interplay between human factors and system design [27]. The field encompasses several key dimensions: explainable AI approaches that generate interpretable recommendations, Human-Computer Interaction (HCI) methodologies that prioritize user agency and understanding, User-Centered Design (UCD) principles that place human needs at the center of system development, and interactive interfaces that enable users to explore, critique, and steer the recommendation process. Recent endeavors, moved from early work on explaining collaborative filtering recommendations [28] to sophisticated visual analytics tool [29, 30], and conversational interfaces [31]. Despite these advances, traditional explainability approaches remain primarily focused on technical transparency and post-hoc explanations, often failing to address the emotional, cultural, and social dimensions of music discovery that are central to human musical experience [6].

2.3. Critical Data Visualization

Critical data visualization represents an interdisciplinary field that challenges traditional approaches to data representation by questioning the power structures, biases, and assumptions embedded within visualization practices [32]. This field encompasses approaches including Data Humanism [33] (pioneered by Giorgia Lupi) and Data Feminism visualization [34] (developed by Catherine D'Ignazio and Lauren Klein). These approaches share a commitment to exposing how visualizations are never neutral; rather, they are deeply political artifacts that can reinforce existing hierarchies or, alternatively, challenge them to promote social justice. Instead of pursuing supposedly objective or universal truths, critical data visualization advocates for situated knowledges, transparent disclosure of design decisions, and visualization practices that empower communities rather than extract value from them [35]. This growing field represents a paradigm shift from efficiency-focused, expert-driven visualization toward more inclusive, reflective, and ethically-grounded approaches that acknowledge visualization as a form of power that can either perpetuate oppression or advance liberation.

The application of critical data visualization principles can potentially address the limitations of traditional explainable AI by centering on human experience. In the case of music, SRS can help in embracing subjectivity in musical taste, and creating interfaces that foster collaborative sense-making rather than individual optimization—approaches particularly crucial in music discovery where personal identity, cultural context, and social connection are fundamental to the experience.

3. Methodology Overview

We implemented a three-step methodology. First, we employed scenario-based design [36] and participatory design [37] to establish user requirements (Section 4) . Second, we employed a design-driven approach that operationalizes Data Humanism principles in the development of HUMMUS, along with five identified requirements (Section 5). Lastly, we evaluate the UX/UI through a mixed-method approach (Section 6). Leveraging our previous work on the characterization of the Data Humanism principles [38], we identify those most relevant to music SRS. This step involved mapping each principle to specific design opportunities, considering both functional requirements and experiential goals.

4. Requirements Identification

We began by creating detailed usage scenarios based on real-world contexts where collaborative music selection occurs, with a primary focus on groups of friends at social gatherings who want to create collaborative playlists that reflect everyone's musical preferences while discovering new songs that bridge their diverse tastes. These scenarios then guided our participatory design session with potential users (N=5) who matched our target audience profile of music listeners interested in collaborative playlist creation and understanding recommendation processes. During this session, participants were asked to envision their ideal music recommendation system and describe what information they would want to see when collaborating on playlist generation. Through this process, we identify the following five requirements:

- **R1. Visual representation of song relationships**: Users require intuitive visual encodings of musical similarities and connections between songs to understand recommendation logic without technical expertise.
- **R2. Temporal understanding**: Users should be able to observe how their musical journey evolves and understand sequential recommendation logic.
- **R3. Transparent recommendation rationale**: The system must provide explanations for why specific songs were recommended, showing the relationship between audio features and algorithmic decisions.
- **R4. Collaborative influence mechanisms**: The system must provide accessible ways for multiple users to collectively steer and influence the recommendation process in real time.

R5. **Serendipitous discovery support**: The system should encourage the exploration of unexpected musical connections while maintaining user agency.

5. HUMMUS

The aim of HUMMUS is to bridge the gap between algorithmic complexity and human comprehension through artistic visualization and collaborative interaction design, targeting two key explainability goals [39]: *transparency* (enabling users to understand how the recommendation algorithm works) and *scrutability* (empowering users to influence and modify algorithmic outcomes).

5.1. Data

We utilized forty thousand songs sourced from Spotify's API [1]. The dataset provides comprehensive metadata including artist information, album details, release dates, and audio features. Through a feature correlation analysis, we decided to focus on five out of Spotify's eleven available audio features: *Energy*, *Valence*, *Tempo*, *Danceability*, *Speechiness*.

5.2. Recommender System

We implemented a lightweight cosine similarity-based approach that prioritizes interpretability and real-time performance over algorithmic complexity. The system computes cosine similarity between songs using the five audio features directly in the PostgreSQL database. The algorithm calculates the cosine distance between the current playlist songs and all songs available in the database. For each recommended song, we identify which audio feature contributes most to the similarity by calculating the absolute differences between features and selecting the maximum. This information is used to explain why specific songs were recommended and supports the flower visualization metaphor. New recommendations are generated dynamically whenever songs are added to the playlist or when the queue becomes empty.

This straightforward approach was deliberately chosen over more sophisticated methods, e.g. neural networks (initially considered LightFM [40]) due to the real-time collaborative requirements and the need for algorithmic transparency that directly supports the flower-based visualization where users can understand how feature similarities influence recommendations.

5.3. Data Humanism for Sequential Recommendations

HUMMUS operationalizes six principles from Lupi's Data Humanism manifesto:

- The **small data** principle guides our approach by prioritizing human-scale narratives, personal connections, and group dynamics over comprehensive musical databases (R1 and R5). It fosters intimate, collaborative data experiences rather than overwhelming users with algorithmic completeness.
- Musical preference represents culturally embedded, **subjective data** experiences, and our system recognizes multiple valid perspectives within collaborative settings, making these differences visible and negotiable rather than eliminating them through algorithmic optimization (R4).
- We encourage **serendipitous data** discovery through exploratory interactions that embrace unpredictability, creating opportunities for musical discoveries from the intersection of algorithmic similarity and human input (R1 and R5).
- Our **design-driven** process ensures that aesthetic and experiential considerations inform the user journey, from collection through presentation, creating coherent and meaningful experiences rather than purely functional interfaces (R3).

[1]https://developer.spotify.com/documentation/web-api

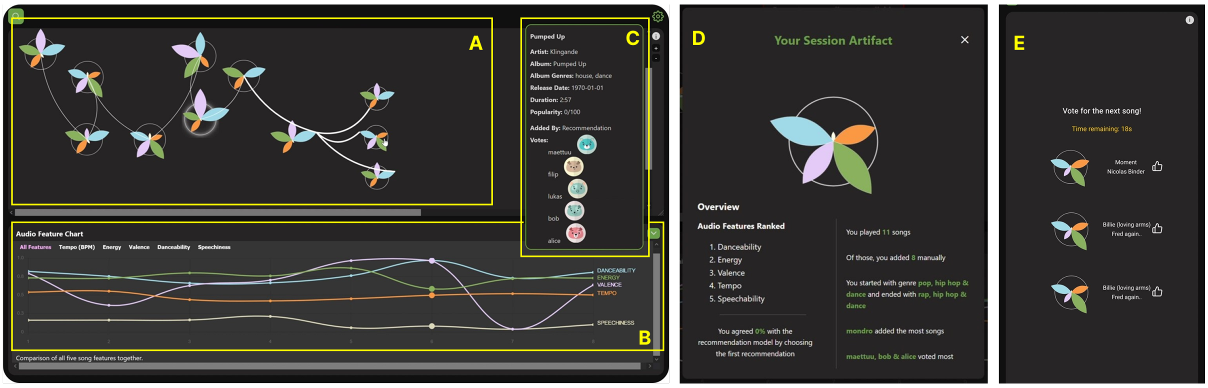

Figure 1: The main interfaces of HUMMUS. The main view (A) displays the sequential *flower garden* visualization, complemented by a line chart (B) at the bottom, which shows the corresponding development of music features over time. A pop-up panel on the right (C) appears when users click on a flower to request song details on demand. The center view (D) shows the final session artifact. The interface on the right (E) demonstrates the use of HUMMUS in the mobile version, highlighting the voting mechanism that supports human-algorithm collaboration.

- The principle of **data to depict complexity** allows us to make intricate algorithmic relationships visible through metaphors and connecting lines, transforming abstract similarity calculations into intuitive visual patterns (R1 and R3).
- Finally, the principle of **spending time with data** allows users to observe how collective preferences evolve, transforming SRS from transactional consumption into collaborative and exploratory sense-making (R2 and R5).

5.4. User Interface and User Experience

User Interface – Unlike conventional interfaces that present songs as static list of items with only text metadata, HUMMUS employs an organic-based visualization that transforms abstract audio features into intuitive visual metaphors (R1, R3). Songs are visualized as a flower, where each flower petal's length represents a song's audio feature value on a 0-1 scale. Different colors indicate distinct features: Energy (Green), Valence (pink), Tempo (orange), Danceability (blue), and Speechiness (white). Flowers are positioned chronologically from left to right, with connecting lines indicating recommendation relationships (R2). The orientation of the flower is adjusted to minimize visual clutter from crossing connection lines. When users vote or select songs, new flowers appear with updated connection patterns, creating a visual narrative of the collaborative journey as visible in Figure 1A. To support real-time collaborative transparency (R4), visual indicators show voting status and subsequent recommendations reflect collective input, making group influence visible in the evolving *flower garden.* A complementary line chart displays audio feature trends over time (Figure 1B), enabling users to observe both individual song characteristics and the evolution of collective preferences.

User Experience – HUMMUS implements a host-guest framework to address the practical realities of collaborative music sessions (R4). Hosts initiate sessions, add seed songs (a minimum of three), and generate shareable QR codes. Guests join via invitation links and contribute songs without requiring an account, addressing both session ownership and barrier-free participation. Users actively contribute songs to the shared queue, and the system facilitates direct song addition and playlist management. When the user-contributed queue pauses, the system automatically transitions to algorithmic recommendation with democratic decision-making supported by a voting system. The voting mechanism serves as the primary interface between users and the recommendation algorithm (R4). This hybrid approach ensures continuous music flow while preserving user agency.

5.5. Explainable Music Experience

When users examine why specific songs were recommended, they can observe the visual similarities between flower configurations and understand how shared features led to recommendation decisions through connecting lines. These connections reveal the algorithmic relationships between songs: when two songs share similar audio feature values, their flowers display comparable petal patterns, and a connecting line appears between the most relevant features showing this relationship. Users can hover over a connection line to see the specific similarity score for each audio feature, providing concrete explanations for why the algorithm considers two songs related (R5). The system's explainability extends to temporal dimensions through the interactive line chart that complements the flower metaphor (R2, R3). The chart reveals how individual audio features evolve throughout a collaborative session, allowing users to explore sequential patterns in their collective musical journey. For example, users can observe whether their group's selections gradually become more energetic or whether valence levels remain consistent over time.

6. Evaluation

We conducted a triangulation mixed-methods evaluation with 19 participants across collaborative playlist creation scenarios [41]. Participants were recruited through convenience sampling and organized into groups of 3-5 members to simulate realistic social music settings.

The evaluation was formed by four phases: (i) system familiarization, (ii) collaborative song selection (minimum 3 songs per participant), (iii) exploration of algorithmic recommendations through voting, and (iv) group discussion of the recommendation process.

6.1. Quantitative

We analyzed user responses, provided through 7-point Likert items, to evaluate HUMMUS's effectiveness in achieving transparency, scrutability, and a positive user experience in collaborative music recommendation scenarios.

Transparency: Participants demonstrated mixed understanding of recommendation processes. While the system effectively helped users comprehend general recommendation approaches (M = 4.68, SD = 1.88), participants struggled with predictive understanding and comprehending the complete relationship between songs (M = 2.84, SD = 1.77). Visual connections between flowers were identified as needing a clearer explanation.

Scrutability: Users generally perceived the system as responsive to their inputs, particularly through voting mechanisms (M = 4.74, SD = 1.85). The collaborative voting feature proved effective, with participants appreciating the group consensus-building process.

User Experience: Participants rated the system favorably on usefulness (M = 4.68, SD = 1.65), ease of use (M = 4.28, SD = 1.90), and satisfaction (M = 4.93, SD = 1.71). Ease of learning received particularly high scores (M = 5.42, SD = 1.25), although error recovery remained problematic (M = 3.58, SD = 1.84). The system generated interesting patterns in group decision-making. However, the balance between individual and group preferences showed inconsistency, with some individuals feeling overrepresented while others felt underrepresented.

6.2. Qualitative

To understand how Data Humanism principles manifested in user experiences, we analyzed participant feedback through the lens of four core design principles, examining both their successful implementation and areas for improvement.

Small Data Implementation: Participants appreciated the focused feature set. P9 noted "I did like the flowers and graphs a lot, especially that each song was shown individually and that you could also filter based on feature." The constrained approach enhanced rather than limited engagement.

Serendipitous Discovery: The flower visualization successfully encouraged exploration, with participants expressing curiosity about visual progression: "It was always like 'How is the flower going to look for the next track?"' The system fostered unexpected connections while maintaining user agency.

Sustained Engagement: Users demonstrated deep engagement with temporal aspects. P17 stated "It was interesting to see how the features of each song were and how it evolved throughout the playlist." The multi-modal design provided multiple pathways for exploration.

Emotional Responses: Participants reported notably positive emotional experiences, describing "joy," finding the experience "very relaxing and calming," and expressing that "it was fun to play around" and "fun to see it evolve." These responses suggest a successful transformation of algorithmic interaction from transactional to genuinely engaging.

7. Discussion and Limitations

Our evaluation demonstrates that artistic metaphors can enhance algorithmic transparency without sacrificing functionality. The flower visualization successfully made abstract audio features interpretable while maintaining aesthetic appeal. However, certain visual elements (flower rotation, connection line meanings) require more precise explanations to maximize the benefits of transparency.

The combination of growing flower gardens and temporal line charts proved effective for supporting both immediate understanding and sustained exploration. This approach could be generalized to other sequential recommendation domains requiring temporal pattern recognition.

Real-time voting during natural interaction pauses successfully balanced individual expression with group decision-making. This pattern could inform other multi-stakeholder recommendation scenarios where consensus building is required.

This work establishes Data Humanism as a viable design framework for recommendation systems. The principles can be effectively translated into algorithmic contexts and could guide human-centered design in other recommendation domains, particularly those involving social interactions or requiring users to understand algorithmic decisions.

Several limitations emerged, highlighting areas for improvement. The reduced database size impacted user trust and diversity of recommendations. Future implementations should prioritize comprehensive music catalogs and genre-aware recommendation strategies. Visualization clarity requires refinement, particularly for connection line meanings and flower rotation systems. Session functionality needs to be expanded to support song removal, re-voting, and session persistence. Lastly, while our evaluation supported groups of 3-5 participants, larger collaborative sessions may require different interaction paradigms and visualization approaches. Future work should explore scalability limits and design adaptations for various group sizes.

8. Conclusion

HUMMUS demonstrates that Data Humanism principles can successfully guide the design of explainable sequential music recommender systems. By transforming abstract algorithmic processes into artistic visualizations and supporting real-time collaborative decision-making, we showed that humanistic approaches can enhance both transparency and user engagement without sacrificing recommendation quality.

Our work contributes to the intersection of explainable AI and music recommendation by establishing design patterns for human-centered algorithmic systems. The flower visualization approach, progressive revelation strategy, and collaborative consensus mechanisms provide generalizable insights for other recommendation contexts that require user understanding and group coordination. The positive emotional responses ("joy," "relaxing," "fun") demonstrate that recommendation systems can move beyond purely functional optimization to support genuine human connection and collaborative discovery. This transformation from transactional consumption to collaborative sense-making represents a significant opportunity for human-centered AI design.

Future work should explore cross-cultural adaptation of Data Humanism principles, integration with existing music streaming platforms, and longitudinal studies of group taste evolution. The framework established here provides a foundation for developing recommendation systems that prioritize human understanding, emotional engagement, and collaborative exploration alongside algorithmic sophistication.

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Declaration on Generative AI

During the preparation of this work, the author(s) used Grammarly to check grammar and spelling. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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