International Journal of Science, Strategic Management and Technology
Volume **02** Issue **03** March-**2026** | ISSN: **3108-1762 (Online)** | Impact Factor: 3.8
An International, Peer-Reviewed, Open Access Scholarly Journal Indexed in recognized academic databases

# Exploring the Interconnections Between Psychological, UX, Algorithmic, and Business Dimensions in Music Streaming Platforms

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**https://doi.org/**10.55041/ijsmt.v2i3.382

**Cite this Article**: Nandi, P. & Manna, S. (2026). Exploring the Interconnections Between Psychological, UX, Algorithmic, and Business Dimensions in Music Streaming Platforms. International Journal of Science, Strategic Management and Technology, *02*(03). https://doi.org/10.55041/ijsmt.v2i3.382



**Abstract.** Music streaming has changed how people listen to music today. In this paper , 30+ studies were reviewed, and that helped to understand how users engage with streaming platforms, how the platforms affects the user behaviour and how these platforms influence behaviour of users. This review focused on important factors such as psychological motivation, emotion regulation and habit formation. It showed that design and recommendation systems effect user engagement. Techniques such as collaborative filtering help to understand user preferences. It was found that recommendation systems increase user experience ,and interface design and psychological motivations effect long term engagement . Also ,the gap between user satisfaction and actual listening behaviours was observed. This study also identified limitations in current research , such as absence of cross-culture and long term studies . This review provided insights for researchers, designers and developers that helped in better understanding of user engagement and music streaming systems that will be developed in future .

**Keywords:** *Music streaming, user engagement, recommendation systems, personalization, collaborative filtering, psychological factors, business models, literature review*

## 1 INTRODUCTION

Ten years ago, music streaming was something that people were using occasionally. Now it has become the main way by which most people listen to music. Many music applications are seen. Some examples of such are Spotify, JioSaavn , Deezer, Youtube Music. They have changed how people access music. It also looks into how well it fits their daily life, their emotions, identity, social habits, and also looks into how artists get paid. As the platforms compete harder and harder for users, researchers have also started asking why people keep using one app, instead of switching between many options.

This paper reviews that research across four areas:

(1) *Why people stream:* Krause et al., Lonsdale and North, and Saad Mohamed et al. [1, 2, 3] used the communication theory which is known as the Uses and Gratifications Theory. UGT helped them to map motivations such as entertainment, mood control, escapism, social connection, habit, identity. Schäfer et al., Chong et al., and Strand Skånland [4, 5, 6] researched about emotional functions of music, and how it helped people cope and regulate their feelings. These days' people are choosing a content library, and at the same time finding a medium for their psychological needs.

(2) *How the interface affects whether people stay or not:* Choi et al., Angela et al., and Venkova and Essien [7, 8 ,9] found that navigation clarity, visibility for personalization , and cross-device consistency , all of these matter a lot for user

satisfaction. Arora et al. [10] extended this to the visually impaired users, and showed that inclusive multimodal design affects a huge chunk of population, as compared to what these platforms are typically designed for. Small interactions such as playlist creation and skip behavior, are important factors for long term usage.

(3) *How algorithms decide what humans hear:* Zeng and Umrawal [11] covers classical filtering, which is a mathematical approach for filtering data. Bendada et al. [12], Xinxi Wang et al. [13], Zhao et al. and Babua et al. [14,15], and Epure et al. and Yun and Lim [16,17] covered the newer approaches such as contextual bandits which are AI decision models rooted in reinforcement learning, and also the emotion-aware models and LLM-based recommendations. Dinnissen and Bauer and Kowald et al. [18,19] put forward the side of rightfulness and it helps to learn about who the algorithm helps to surface , who the algorithm leaves out, and how that helps to connect to artist revenue.

(4) *How business models shape everything else:* Bergantiños and Moreno-Ternero [20] provided some insights about revenue sharing. Xu et al. [21], Han [22], and Hsu et al. [23] covered topics such as co-creation, community engagement, and what drives users to upgrade. Zhang and Zhang and Li et al. [24, 25] also found that trust and perceived fairness predict rates of long-term retention more reliably, as compared to music app features.

Also it was seen that all these four areas are not independent. User engagement in music streaming is influenced by all of them working together, or all of them failing at the same time. Thus, it can be said that the important factors are -

*1. Psychological needs and motivations*
*2. User experience and interface design*
*3. Algorithmic personalization and system intelligence*
*4. Business models, fairness, and economic incentives*

Despite extensive research across these domains, existing literature remains very fragmented and unconnected. It is seen that psychological studies rarely integrate UX findings, and that algorithmic research rarely integrates behavioral factors inside it. So the goal of this review is straightforward .The goal is to bring these four areas together to understand what actually makes people continuously use music streaming apps. These will be answered together, here, instead of one at a time.

Four questions guide the review:

- *RQ1:* What psychological and motivational factors shape how people use streaming apps and whether they keep coming back?
- *R*Q2: How does interface design, usability, and accessibility affect whether users feel satisfied or not?
- *RQ3:* What do recommendation algorithms and AI-based personalisation actually do to the user experience?
- *RQ4:* How do business models and revenue fairness affect trust, loyalty, and whether platforms survive or not?

Here, the focus is on answering these together, rather than one at a time .This is what makes this review different from most of the individual studies in this area.

## 2 METHODOLOGY OF LITERATURE REVIEW

This review uses a transparent multi-stage methodology to find the key insights from 30+ peer-reviewed studies, which are related to music streaming, user psychology, UX design, algorithmic personalization, etc. The objective is to create a coherent theoretical framework that helps to understand intention to continue and engage on modern music streaming platforms.

### 2.1Paper Selection Strategy

Academic papers were identified by use of some major databases for scholars -*Scopus, Web of Science, Google Scholar, IEEE Xplore, Science Direct, Taylor and Francis, ACM Digital Library, IEEE Xplore, and Springer Link.*

A combination of specific keywords was used, such as: "music streaming", "intention to continue", "uses and gratifications", "music recommendation systems", "UX evaluation", "algorithm-based personalization", "emotion-aware music recommendation systems", "fairness in recommender systems", "platform business models for music", "LLM recommendations", and "user engagement in digital music."

*Criteria for inclusion:*

- Journals and conference papers need to be reviewed by peer scholars
- Papers that were published between 2000 and 2025
- Directly about digital music platforms
- Psychological, UX, algorithmic and business focus
- Full text was available in English

*Criteria for exclusion:*

- Papers about audio signal processing with no dynamic of users
- Music research related papers that are unconnected to streaming
- Duplicate papers across the databases

### 2.2Categorization Framework

Each of the papers was read and placed, into one of the four categories, based on its main contributions.

1. *Psychological Factors:* Motivation, gratifications, emotion regulation, identity, satisfaction
2. *User Experience (UX):* Interface design, accessibility, cross-device use, usability
3. *Algorithmic Personalization:* Collaborative filtering, deep learning, reinforcement learning, LLMs, emotion-aware systems, fairness
4. *Business & Platform Factors:* Revenue models, co-creation, loyalty, fairness in payments and royalty, market dynamics

This classification formed the basis for drawing the inference and is presented in later sections.

### 2.3Data Extraction & Synthesis

The five important fields, which made it possible to spot patterns and gaps are:

- *Paper ID*
- *Full Title and Authors*
- *Category*
- *Methodology*
- *Key Findings*

### 2.4Comparison Table

A table of comparison helps to quickly understand:

- *Where the research came from:* How many studies were done in different areas or topics.
- *Different ways in which the research was done:* The variety of methods such as surveys, interviews, or experiments that are used by the researchers.
- *The big lessons that were learnt:* The main findings that helped to build the final theory

Table originally presented an overview of 30+ peer-reviewed studies about music streaming platforms, and that table was organized by index, full title and authors, categories such as psychology, UX, business, algorithms , methodologies such as surveys, text mining, literature reviews, etc., and key findings. Some of the important papers that were studied include the ones written by Krause et al. [1], which was written about social gratifications and mood gratifications, Schäfer et al. [4],

International Journal of Science, Strategic Management and Technology
Volume 02 Issue 03 March-2026 | ISSN: 3108-1762 (Online) | Impact Factor: 3.8
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which was written about emotion regulation. It was observed the paper by Bendada et al. [12] was about contextual bandits which are used to make optimized decisions , Wulandari et al. [26] which is about whether users kept coming back, and Chung et al. [27] which is about interface problems that were identified through user reviews.

Table 1: UX Evaluation Methods and Key Findings across Studies

| **Study** | **Authors** | **UX Focus** | **Methods** | **Key Findings** |
|---|---|---|---|---|
| *Exploration of User Engagement on Spotify* [3] | Mohamed et al. | Engagement features | Survey + qualitative analysis | Playlist tools and social features enhance the engagement experience. |
| *Everyday Music Listening and Affect Regulation* [6] | Skånland | User Experience during effective use | Ethnography / interviews | Users require fast, reliable access for the emotion-regulation activities. |
| *Towards a New Interface for Music Listening: A UX Study on YouTube* [7]. | Choi, Shin, Joung, Lee, Lee. | Interface issues related to music-listening | Qualitative users study ; prototype testing is done | Video first UI disrupts for only-music tasks; requires listening-centric redesigning |
| *User Experience Evaluation on Music Streaming Applications with UEQ Method* [8] | Angela, Halim, Pramana, Simanjuntak | Usability, attractiveness, stimulation | Quantitative evaluation by the use of User Experience Questionnaire | Lowest-performing dimensions are stimulation and novelty; humans need for a broader – scope of interaction. |
| *Optimizing User Experience Across Platforms* [9] | Venkova & Essien | Cross-device continuity | Multi-device UX study | Consistent interaction increases perceived usability and trust. |
| *Music Apps on Mobile and Computers: A Critical Review on Spotify* [28] | Singh & Pande | Usability & transparency | Critical review | Highlights strengths of discoverability, also shows explanations about weak accessibility & poor algorithms. |
| *Deep Learning Approach for Music Genre Classification* [29] | Asanah & Pratama | Metadata-driven UX | Deep learning experiments | Better genre tagging for songs improve UX for song discovery. |

## 3 PSYCHOLOGICAL AND MOTIVATIONAL FACTORS IN MUSIC STREAMING

Streaming behavior is mostly driven by psychological needs. This explains adoption, engagement, and long-term loyalty about music streaming .And emotion and identity are big driving factors behind it.

### 3.1 Uses & Gratifications in Music Engagement

UGT (Uses & Gratifications Theory) explained streaming through needs of users which are mood control, identity and social connections. It is a useful model but it has limitations. Algorithms are very important because they decide what people hear, but they can constrain choice and limit user agency. The reality shows constraints and problems that are not seen in theory.

The takeaway is that though emotional and social needs drive use, platform designs control the satisfaction for these needs.

### 3.2 Emotion Regulation and Mood Management

It is known that music helps people to feel better. It is used for stress relief, mood repair, comfort, work focus. This finding is consistent across every study and every age group. But one of the main problems here is measurement, a good example to understand this is how different studies define emotion regulation differently.

The takeaway is that emotion regulation is the most consistent driver in this literature, but shared measures are still needed.

### 3.3 Pleasure-seeking and Purpose-seeking Motivations

Listening is not just enjoyment for people. Hedonic listening is pleasure-seeking listening. Purpose-seeking listening is about meaning, reflection and growth. It is observed that when platforms optimize only for listening time, they are not able to understand these kind of pleasure -seeking and purpose-seeking motivations of listening.

### 3.4 Habit Formation, Intention to Continue, and Loyalty

It is known that habits are built through repetition. Satisfaction can bring the users back once, but familiarity brings them back repeatedly. That is why when service quality or perceived value drops, the habit breaks immediately.

### 3.5 Comparisons, Agreements, and Contradictions

*Agreements*

- Emotion regulation is the primary motive
- Identity and social gratifications remain consistent factors
- Satisfaction predicts the intention to continue

*Contradictions / Gaps*

- Algorithms may restrict user agency or the user's autonomy
- Emotional measures lack standardization so cannot be applied universally
- Survey-based methods try to oversimplify motivations

*Sample & Method Limitations*

- Student-biased samples reduce universality
- For qualitative depth of understanding ,absence of prediction is seen
- Under usage of cognitive models is seen

## 4 USER EXPERIENCE & INTERFACE DESIGN

UX (User Experience) is not just about the frontend design that is seen. It also determines whether people can actually use the app comfortably, across the different devices and different contexts.

### 4.1 UX Evaluation Methods in Music Streaming Research

Skånland [6] found that predictable, no-resistance access mattered most during emotional type of listening. Choi Shin et al. [7] showed that video-first interfaces creates friction for experiences that should be music first. This is because audio-first features like background playback and simplified navigation help, matter the most .Angela Halim et al. [8] used UEQ (User Experience Questionnaire) and found that when repetitive layouts and weak feedback are used, it reduces engagement. Venkova and Essien [9] found that continuing with state syncing mechanisms allow continuing from where the users left off across devices, and that directly improves trust.

*Comparison:*

• Quantitative tools find the gaps in usability
• Qualitative approaches explain the importance of emotional needs

Together, UX is functional, conceptual, and dependent on context.

### 4.2 Accessibility and Multi-Platform Design

There are many platforms that do not work well for everyone. Arora et al. [10] showed the barriers and problems for visually impaired users and showed that multimodal navigation is needed, which is tactile or touch-based, auditory, and gesture-based. Singh and Pande [28] also demonstrated that though people are familiar with Spotify, it is not fully transparent and accessible for new or impaired users. The two gaps that stand out are -

1. Limited multimodal interaction
2. Inconsistent UI across devices

This is why high-quality design principles are needed.

### 4.3 UX Impact on Engagement, Discovery, and Satisfaction

Interface design directly affects engagement and retention levels. Community-oriented features such as playlists, sharing, editorial content, help to increase association and activity levels. Improved genre tagging and recommendation systems help to accelerate discovery. It is also seen in case of poor navigation and weak search, there is lower trust and satisfaction.

**Overall Insight:**

Clear navigation, accessible design, cross-device continuity, and good discovery tools increase engagement and perceived value consistently.

Table 2: Comparison of Qualitative and Quantitative UX Studies

| Approach | Strengths | Examples | Limitations |
|---|---|---|---|
| Qualitative UX studies (study of ethnic groups in anthropology, interviews, task-based studies) | Learnt about lived experiences, context-based challenges, emotional interactions | Skånland Choi et al.; [6,7] | It can be hard to generalize; small sample sizes |
| Quantitative UX surveys (User Experience Questionnaire, structured questionnaires) | Found measurable results, it allows comparison across apps, identifies issues about usability | Angela et al.; Venkova & Essien[8,9] | Overlooking of contextual and emotional factors; interpretation is rigid |
| Hybrid / data-driven UX studies | Helps to connect real usage patterns with UX perceptions | Chung et al.; Asanah & Pratama [27,29] | Dependent on the platform- provided data |

### 4.4 Gaps in UX Research

1. It is observed that almost no cross-cultural work exists. Most studies focus on Western or East Asian users, and Indian, African, and Middle Eastern users are barely represented
2. It is observed that that accessibility is almost unstudied topic. Arora et al. [10] gave representation to visually impaired users through their work. Users with motor, cognitive, or auditory issues remain mostly unstudied.
3. In most cases, algorithmic transparency is not treated as a UX problem. This area of research is also important because users regularly ask why the app recommended something.
4. Long-term studies do not almost exist. All the papers here try to measure satisfaction at one point in time. So it is difficult to be sure about whether good UX actually keeps people loyal over months or years.

## 5 ALGORITHMIC & RECOMMENDATION SYSTEMS

Algorithmic recommendation systems create the foundation of music-streaming platforms. It influences how the users discover, how they engage, and how satisfied they are with the outputs. Earlier, traditional content-based and collaborative filtering models were used and now modern deep learning, reinforcement learning, emotion-aware computing methods are used. This shows that listeners are very dynamic, and they have different motivations to listen.

### 5.1 Traditional Recommendation Approaches: Content-Based & Collaborative Filtering

Earlier systems used filtering methods that were content-based and collaboration-based. Sometimes, a combination of both was also seen. Reviews by Zeng Umrawal [11] showed that systems like audio feature engineering and matrix factorization were used to make the results more relevant. Despite that problems like sparse data, slow start of applications due to lack of sufficient data, and lack of sensitivity to context were seen.
Industry research of Deezer application was done by Bendada Salha Bontempelli [12]. It showed that contextual bandits adjust rankings based on live feedback, and this helped to get better click- rates and session engagement. But even with these improvements, traditional models mostly ignore the emotional and situational factors. They forget to take the fact into consideration that user preferences change with time.

### 5.2 Advanced and Adaptive Approaches

Recent works have showed that richer contexts and psychological signals help in developing personalization algorithms.
Reinforcement learning (RL) approaches, such as the one cited by Wang Hsu Wang [13], showed this. It showed that recommendation is a step-by-step process, and the focus is on keeping users engaged over time .The main focus is not getting immediate clicks. This allows some exploration. RL also becomes able to support users whose tastes shift over time.
Emotion-aware models are also used, they allow to use mood signals to match music with how the users are feeling in real time. The studies by Zhao Liu Zhang [14] and Babua Nair Geetha [15] are observed. These showed that mood-sensitive recommendations feel more relevant and satisfying for the users, because they connect directly to the emotional needs of the users. LLM-based systems were researched by Epure Schedl Moussallam [16] .They use understanding of language to read natural-language queries and to understand what the users actually want. These models make conversations much smoother and clearer. But there are certain problems attached to it such as computing costs, reliability in matters of evaluation, and the risk of generating wrong information.
Socially-aware and graph-based systems are used, as cited by Ziaoddini [30]. This showed that how people listen to music is related and connected to their social world. These approaches helped users to discover more and get a stronger sense of belonging with the music applications.

### 5.3 Cold-Start Personalization

New users come with very little data, and that makes personalization very hard. Hybrid approaches were proposed by Briand Salha-Galvan [31]. Here ,combination of broader behavioral patterns with the limited interaction data that is available, is observed. It helps users to find satisfying content faster.

### 5.4 Psychological and UX Implications

Across studies, a clear pattern was seen:
• Traditional Collaborative Filtering improved basic relevance
• Emotion-aware systems support mood regulation
• LLM and conversational models enhanced clarity and trust
• Reinforcement Learning and social approaches encourage exploration and identity expression

So recommendation designs are built around psychological needs and UX goals, with a focus on human-centered personalization.

### 5.5 Evaluation and Gaps

For most research, private datasets are used. This makes it harder for others to verify results. Thus, the measures that are commonly used are accuracy, ranking quality, engagement, diversity, and fairness. But several gaps remain. Problems such as cross-cultural testing, inconsistent benchmarks, weak tracking of the long-term psychological outcomes and small attention spans for accessibility, are seen.

## 6 BUSINESS MODELS & PLATFORM STRATEGIES

Business models make a strong contribution to how the platforms create and share value. Business models also have a strong effect on user trust, engagement, and how the algorithms are built. The literature points to three connected themes which are revenue-sharing and fairness, user co-creation, and niche-market strategies. These elements are combined with UX and recommendation systems to influence long-term loyalty.

### 6.1 Revenue Sharing and Fairness

Economic analysis was conducted by Gustavo Bergantiños and Juan D. Moreno-Ternero [20]. It was seen that standard, ratio-dependent payout models put independent artists at a disadvantage. User-centric alternatives are considered to be better, because revenues are distributed more fairly there. Studies about governance was conducted by Ola Haampland [32]. Thus it can be said that being open about how monetary compensation works , helps to build trust between artists and platforms. So fairness in payouts has direct impact on how satisfied people are.

### 6.2 User Co-Creation and Community Engagement

Streaming platforms depend heavily on things that users do, such as making playlists, sharing them, and building them in a collaborative way. Research by Jinghong Xu [21] and Lu Han [22] also showed that these activities create a sense of belonging and emotional investment. Case insights from Spotify also showed that community playlists and social features help people find new music but also keep them coming back and help them feel connected to the platform. Co-creation turns users from passive listeners into active participants.

### 6.3 Niche Markets and Beyond-Mainstream Listening

Listeners who listen to niche music are a particularly important group for platforms. Studies by Dominik Kowald [19] also showed that these users are strongly motivated by identity and stay very loyal when they see that the platforms give the opportunity for personalized recommendations. Massimiliano Raffa [33] showed ethnographic findings, which helped to learn that algorithmic transparency and good discovery tools are essential, for users to feel happy and engaged. In conclusion, it can be said that personalization, fairness, and community features are very essential for bringing in niche audiences.

### 6.4 Integrated Perspective

One connected system is built out of business models, UX design, psychological motivations, and algorithms. Fair revenue structures help to build trust, and easy-to-use interfaces reduce fear of technology, and adaptive recommendations are used to make content feel more relevant. Together, they create positive feedback loop for the users. When the system becomes more restrictive, users remain unsatisfied. Platforms become successful when they ensure economic fairness and prioritize the experience of their customers.

## 7 INTEGRATED DISCUSSION & SYNTHESIS

Psychological motivations, UX design, algorithmic structures, and business strategies all work together and they have an effect on each other. This section brings these factors together to highlight the main trends.

### 7.1 Cross-Domain Connections

Work done by Krause; Lonsdale & North; Schäfer [1, 2, 4] showed that users come to streaming platforms with their psychological needs, which are about identity, emotional regulation, and social connection. These motivations shape what users expect from User Experience. After reading the research papers by Choi et al., Angela et al., and Rahul Singh and Ruchimita Pande [7, 8, 28], particular inferences were drawn. Design choices like navigation, accessibility, and consistency across devices have an effect on satisfaction. Algorithmic studies, range from traditional methods by Terence Zeng & Abhishek Umrawal [11] to advanced LLM work by Epure et al. [16] and Reinforcement Learning by Xinxi Wang et al. [13] .This shows that personalized systems are dependent on factors like familiarity, novelty, emotion, transparency and control. At the same time, business models influence metrics algorithms which are built to optimize for short-term engagement, diversity, and fairness principles.

### 7.2 Trends and Points of Agreement

- *Emotion regulation* is a central theme across psychological, UX, and algorithmic studies like the studies conducted by Chong, Hsu, Babua [5, 13, 15].
- *Personalization* remains the most powerful predictor for satisfaction and loyalty, in different domains.
- *Transparency and fairness* are very important for users and creators, and affects trust.

### 7.3 Contradictions and Tensions

- When algorithms are highly personalized it can improve satisfaction but reduces user agency and autonomy, as mentioned by Raffa [33].
- Fairness models that benefits artists can cause issues for platform revenue.
- Increasing complexity of algorithms (LLMs, RL) improves relevance but causes risk-related vagueness and bias

### 7.4 Identified Research Gaps

1. *Lack of inter-cultural UX studies and studies about motivation factors* - most samples remain Western or region-specific.
2. *Limited integration of AI-based personalization with psychology-based models* - few studies bridge the gaps between emotion regulation, cognitive needs, and algorithmic design.
3. *Absence of long-term analysis* **-** of patterns of engagement is seen , an exception is

Sunghun Chung's [34] large-scale study.

4. *Gaps in Accessibility* - despite the contributions by Lauryn Arora et al. [10], integration into mainstream platforms remains limited.

## 8 CONCLUSION & FUTURE DIRECTIONS

This review helped to understand that user engagement in the music streaming platforms is influenced by psychological motivations, design of user experience, and algorithm-based personalization. Emotional needs, habit formation and listening that is driven by a sense of identity effect long term usage. Also at the same time, design of interface, accessibility, and consistency in cross-device patterns effect long term retention amongst users. While the recommendation systems improve relevance levels, a gap is seen between user satisfaction and actual listening behaviour. This can happen due to design choices in platforms and business strategies. In conclusion, music streaming platforms are interconnected systems where technological, psychological and economic factors play a vital role.

### *Future Research Directions*

1. *Multi-modal UX research*

Multi-modal user experience design is needed where integration of visual features , auditory features and context-awareness are seen.

2. *Emotion-aware personalization that is based on AI/LLM*

Combined approaches are used that consist of LLM language understanding, affective computing, and established psychological theories.

3. *Accessibility and inclusion as core design priorities*

Most current studies do not treat assistive technologies as central elements, they are treated as add-on accessories. Future work should try to rethink accessibility for visually-impaired and neurodivergent people.

4. *Long-term and real-world behavioral studies*

The field is missing long-term data that helps to understand how habits, re-listening behaviors, social practices, and loyalty change over months or years.

5. *Frameworks for all-rounded fairness and integrity*

Future work should develop fairness models, where the perspectives of creators, users, platforms, and communities are taken into consideration, for better royalty distribution and monetary shares.

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