Beyond the Algorithm: How Users Interpret and Navigate Music Recommendation Systems on Streaming Platforms

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Master Thesis Class Arts, Culture and Society (CC4008)

Master of Arts, Culture and Society
Erasmus School of History, Culture and Communication
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Word Count: 15750 words

13/06/2025

ABSTRACT

This thesis explores how users of music streaming platforms interpret and navigate their algorithmically mediated listening experiences. While much of the existing research foregrounds the technical design of these systems and their broader implications on music consumption, this study shifts the focus to the listener's perspective. Drawing on semi-structured interviews with 14 participants from Italy and Sweden, the research explores how individuals make sense of algorithmic recommendations in relation to their listening habits, sense of autonomy, and evolving identities as listeners.

Employing inductive thematic analysis, this study identifies recurring patterns in how users engage with algorithmic curation. The analysis highlighted tensions between trust and skepticism, serendipity and control, and automation and self-expression on the part of the users. The findings reveal that users actively engage with music recommender systems (MRS), at times embracing, questioning, or often adapting them to fit their personal listening routines. Participants frequently described their emotions in relations to their experiences on music streaming platforms, highlighting the importance of considering the emotional and interpretative layers in the elaboration of algorithmic mediation experiences.

By foregrounding the perspectives of users, this thesis contributes to a more granular understanding of how recommendation algorithms are experienced in everyday musical life. It underscores the agency of listeners, considering them as critical actors who interpret, appropriate, and at times resist algorithmic influence in ways that reflect both personal and cultural meanings of music. Finally, this research aims not only at deepening our understanding of how users engage with algorithmic systems, but also at informing more nuanced, human-centered approaches across disciplines. In addition, it seeks to encourage methodologies and designs that account for lived experience, support user autonomy, and critically reflect on the cultural and psychological dimensions of algorithmic mediation.

KEYWORDS: use-centric approach, music streaming platforms, music recommender systems, music lovers, music discovery, user agency

Word count abstract: 284

Acknowledgements

To my mum,

I am deeply grateful for your endless support, even if supporting my life choices means living far away from each other. During my study period, for every inconvenience, you were always there for me, even if far away, and were always ready to remind me how strong I am and how lucky I am to have you in my life.

To Carl,

You are always by my side, even in the rainy and cold Netherlands you reminded me that warmth can be found where love is. I wish to us the best possible future together.

To my friends,

Thank you for your love, I could not feel more loved and special thanks to you. Even when I was away from home it always felt like I had you with me. I am extremely grateful for all the insights and interesting points you raised when talking about my project. You never cease to remind me how lucky I am to have such incredible people in my life.

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1. Introduction

The digital transformation of music consumption has fundamentally reshaped how listeners engage with music. Streaming platforms such as Spotify, Apple Music, and SoundCloud have become the primary gateways for accessing and discovering music for millions worldwide. Unlike traditional media where music selection was largely curated by radio DJs, record stores, or personal collections, today's listeners increasingly rely on algorithmic recommendation systems (MRS) to guide their listening choices. These systems generate personalized playlists and suggestions based on complex data analysis of user behavior and preferences, significantly influencing the musical landscapes available to individuals.

Research has far investigated the relationship between human and non-human actors, highlighting how technologies actively participate in shaping social practices, rather than merely serving as passive tools (Latour, 2005). Particularly, Actor-Network Theory explores how non-human entities, including technologies, actually co-produce action and meaning within networks, actively shaping social practices and with social phenomena being formed through interconnected relationships between human and non-human actors (Latour, 2005). In parallel, cultural sociologists and media scholars have developed theories of technological mediation that emphasize how digital technologies shape not only behaviour but also subjectivity and identity formation. In doing so, they are not only mediating what people consume but also how they construct meaning from their experiences and therefore also their sense of self (Beer, 2013; DeNora, 1999; Beauscart et al., 2019). Although these studies present important features and characteristics of algorithmic systems in music streaming platforms, they mostly focus on what the users are exposed to.

Recent research on algorithmic mediation has examined the ways in which recommendation systems also shape users' consumption patterns, emphasizing how algorithms filter and prioritize specific kinds of content and how this affects the listening behaviour of the users (Seaver, 2017; Eriksson et al., 2019; Celma and Cano, 2008). Hence, research most often focuses on music discovery, user engagement and choice, frequently categorizing user types or quantitatively assessing the algorithm's influence on consumption patterns.

However, less is known about how individuals make sense of their experiences on music streaming platforms with algorithmic recommendations systems: how they reflect on, re-elaborate and engage with these systems in their everyday use. Rather than assessing what users consume, this study shifts the attention to how individuals consume, interpret and perceive the algorithmically mediated nature of their listening practices.

Therefore this study asks:

How do music streaming users make sense of and engage with recommendation systems in their listening habits?

Using a qualitative method, based on 14 semi-structured interviews and a subsequent thematic analysis, this research aims to delve into the relationship between users and music recommendation systems in streaming platforms, through a user-centered perspective.

The findings reveal that users do not passively follow algorithmic recommendations. Instead, they actively make sense of them in relation to their own taste, habits, moods, routines and social contexts. Many participants described moments of surprise, frustration, or delight that shaped their ongoing relationship with the platform and their sense of musical self. This underscores the importance of considering listening as a deeply personal and dynamic process. In the case of algorithmic recommendations and music streaming platforms, one that is co-shaped by both human intentions and technological mediation.

Investigating these topics under a more personal lens can lead to many benefits for researchers in Media studies, Sociology, Music Psychology and even more technical fields like UX research or Science and Technology Studies. First of all, it would grant a greater recognition of user agency, highlighting how people actively shape their listening practices and digital identities within algorithmically mediated environments, without forgetting that both users and technologies are active participants in the same network, as theorized by Actor-Network Theory. Users are therefore considered not as passive recipients of algorithmic recommendations, just as algorithms are not neutral intermediaries, and both co-produce meanings from their reciprocal interaction.

Moreover, this research moves beyond personality-based or user-types models, aiming to capture the subjective, contextual and identity-related dimensions of musical experience. This can possibly help in designing psychological studies that consider interpretative engagement with music in digital contexts, incorporating the real-life dynamics of platform use. Furthermore, it offers a grounded perspective on how technologies participate in an individual's everyday cultural life. In addition, it can help redesign recommendation interfaces that feel more transparent, responsive and respectful of user goals, integrating more customizable features. This would motivate a shift of the platforms' focus from efficiency to meaningful engagement, a firm ethical grounding and trust-building, always respecting the users individual autonomy.

To unpack how people live with and through recommendation systems, the literature review begins by centering the user: their sense of agency, the diversity of their listening practices, and the meanings they attach to music in everyday life. This includes examining how users interpret, adapt to, and sometimes resist algorithmic suggestions, foregrounding their role not merely as recipients, but as co-participants in shaping their digital listening environments.

The literature review then explores the intricate entanglements between humans and technologies, showing how these relationships are co-constructed through ongoing negotiations, context, and feedback. Emphasis is also placed on the limitations of current systems that rely on fixed user profiles or opaque inferences, and on the need for more transparent, adaptive, and user-informed design. Only after grounding these dynamics does the discussion turn to the inner workings of music recommender systems, not as neutral engines of efficiency, but as active agents in shaping musical experience, with the potential either to narrow or to expand the cultural and emotional landscapes users inhabit.

2. Literature Review

2.1. A User-Centric Approach

A growing body of research emphasises the importance of designing algorithmic systems, and even streaming platforms more broadly, keeping the user always at the center of the attention. Prioritizing the needs of the user would lead to higher degrees of satisfaction, keeping in mind the different motives and situations in which users engage with music streaming platforms.

2.1.1. Personalizing Recommendations: Accounting for User Diversity and Listening Contexts

For instance, analysing aspects of the users' music-related psychological traits (Tang & Jhang, 2019, 540-552), like music involvement, music identity, preference diversity and preference openness, could help in creating different classes of users from which the creation of personalized recommendation strategies could be considered. As not everyone uses and values music the same way, this would help in moving beyond a one-size-fits-all logic.
To implement different recommendation mechanisms for distinct user classes would certainly achieve higher satisfaction levels. For instance, a person who is deeply invested in music**,** or who perceives music as essential to their identity, is likely to be more selective about what they listen to. A music lover, for example**,** will try to check and control the sources of what he listens to and will engage in music listening sessions also by himself (Tang & Jhang, 2019), reflecting on the deeper meaning of musical content. In contrast, more casual users are likely going to listen to music mostly in social situations and trust editorial guidance to discover and consume music (Raff & Strauss, 2020).

Additionally, research has shown that even personality traits have a great impact on what people listen to, showing that extroverted people are more likely to prefer upbeat and conventional music while introverts prefer more niche and "deep" artists and songs (Rentfrow & Gosling, 2003, 1236-1256). These findings further illustrate the variability of user needs and the necessity of accounting for such differences when designing recommendation systems.

Notably, what this research wants to highlight is the idea that music streaming platforms and MRS may not be judged universally and univocally, according to a single model of use or success. Instead, they must be understood as tools that individuals engage with in highly personal, context-dependent ways. This is the reason why delineating and structuring both platforms and MRS starting from the user would ultimately be effective, creating a platform that is truly reactive to the user and does not answer to market logics, random assumptions or technical abstractions.

2.1.2. Moving Beyond Accuracy: Understanding User Intent and Satisfaction

While algorithmic approaches are designed to optimize user satisfaction, they often rely on abstract metrics, like coverage, ranking or accuracy, rather than a grounded understanding of the user intent. This creates a situation in which the system is forced to 'guess' whether to prioritize novelty or familiarity, without direct input from the user. While users themselves may not always be fully aware of, or able to clearly articulate, their musical needs or intentions, current systems still tend to marginalize these complexities. As a result, algorithmic assumptions often take precedence over the more nuanced, situational nature of listening, which is shaped by shifting preferences, emotional states, and contextual cues.

Of course abstract metrics serve a purpose, but they are insufficient on their own (Garcia-Gathright et al, 2018). Moreover, these processes are typically opaque to users. When the logic behind recommendations is unclear, trust is harder to establish. This lack of transparency is closely linked to user satisfaction and the extent to which users are willing to "forgive" irrelevant or inappropriate recommendations (Afchar et al., 2021, p. 190). Traditional evaluation methods, which often rely on quantitative metrics, fall short in capturing the full complexity of user satisfaction and the perceived quality of recommendations. As Fazeli et al. (2012, p. 442) argue, "subjective system aspects and experience variables are invaluable in explaining why and how the user experience of recommender systems comes about," highlighting the need for more user-centered approaches in assessing recommender performance.

If much of the criticism surrounding music recommender systems (MRS) focuses on the methods used to generate recommendations, often seen as overly quantitative and detached in how they construct user profiles (Schedl et al., 2018), then one potential response lies in the adoption of “beyond-accuracy” evaluation metrics. Metrics such as novelty, serendipity, and diversity offer alternative ways to assess recommendation quality by prioritizing user experience and discovery, aiming to find those items that are most interesting to a user (Adiyansjah, 2019), rather than purely predictive performance.

2.1.3. Embracing Novelty and Serendipity: Expanding the Horizons of Music Discovery

At this point, it becomes important to introduce the concepts of serendipity and novelty, both related to the concept of discovery. While their definitions may vary, serendipity has been generally defined as the ability of the system to recommend items that are novel, unexpected and useful (Kotkov et al, 2016, p.181), while novelty is defined as the ability of the system to recommend items that are unknown to the user (Vargas & Castells, 2011).

Novelty has been found to play a key role in recommendation systems for two main reasons. First, the very notion of recommendation implies the concept of discovery, allowing users to be exposed to content they would have not found on their own. Second, as Vargas and Castells note, "avoiding a too narrow array of choice is generally a good approach to enhance the chances that the user is pleased by at least some recommended items" (2011, p.110). However, novel items can be both relevant and irrelevant to the user, with the recommendation effectiveness depending on how well it aligns with the user's shifting interests and context.

Serendipity, on the other hand, is even more complex, involving a high degree of subjectivity and emotional resonance. This makes it difficult to measure, to compute and implement into algorithmic programming. For a recommendation to be perceived as serendipitous, it must be not only new but also meaningfully surprising and personally engaging (Kotkov et al., 2016). These attributes are therefore hard to quantify, as indicators like interest and unexpectedness are far less straightforward to capture than more conventional measures such as accuracy. Furthermore, being serendipitous is not only an inherent property of the item itself, but also requires a degree of *mind-preparedness* on the part of the user. That is intended as a readiness to notice, accept, and find value in the unexpected (Corneli et. Al, 2014). In the case of MRS, this readiness is shaped by the user's expectations of receiving suggestions aligned with his profile. When a suggested item breaks from those expectations yet still resonates, the result is not just surprise, but a meaningful discovery. Serendipity, therefore, is not aligned with accuracy-based evaluations (Ziarani, 2020, p. 377), but instead offers a promising path to overcome the problem of over-specialization, as to say a "landscape" of suggested items too similar to the user's past preferences.

Thus, both novelty and serendipity can be classified as qualitative measures and, even if they are important to fully capture user engagement and satisfaction (Schedl, 2018, p.106), they are not easy to implement in MRS. Despite these challenges, their integration in MRS would be crucial in improving user engagement and the appeal of algorithmic recommendations. Novelty plays a key

role as it introduces new content, preventing monotony, while serendipity ensures that novelty is not only unexpected by definition, but also relevant. This would ideally ensure a higher degree of engagement with the platforms and, in general, a stronger desire to discover unfamiliar items. Also, they both would help in combating the idea of the filter bubble, in which many users feel entrapped because of overly personalized and repetitive content.
Nonetheless, the pursuit of novelty and diversity must be balanced carefully, as irrelevant recommendations can also stir users' dissatisfaction. Moreover, novelty and diversity could be seen as a potential trade-off with system accuracy (Hurley and Zhang, 2021), as they try (especially serendipity) to steer away from familiar content.

2.1.4. Centering the Listener: The Case for User-Driven Algorithm Design

Finally, numerous researchers have highlighted the importance of placing the user at the center of recommendation system design (Burke, 2002; Ferwerda et al, 2016; Tang & Jhang, 2019), arguing that this approach would be more effective than just relying on the algorithm to "guess" whether to prioritize novelty, similarity or accuracy, without a direct and resourceful input from the user. Current methods, often depending on inferred preferences, may also incur in the risk of marginalizing the importance of the agency of the user, placing algorithmic assumptions at the center of the focus. Yet, an algorithm can only function properly and be truly effective in its end only if it satisfies the users' desires, making it essential to foreground individual experiences, evolving preferences and contextual needs.

For instance, de Oliveira et al. (2023) advocate for user-centered approaches that incorporate contextual information and dynamic user feedback, arguing that successful recommendations require ongoing adaptation to shifting listener preferences. Similarly, Gabbolini and Bridge (2022) propose alternative frameworks such as "personal music tours," demonstrating how user interviews and experiential insights can inform algorithmic design, ensuring that systems reflect the complexity and richness of individual listening practices. These studies underscore the value of grounding technological systems in the rich, subjective experiences that users bring to their everyday engagement with music.

In conclusion, it results is that the central focus remains the users themselves, without whom the algorithm would lack the contextual foundation to function meaningfully. This concerns not only the specific items they consume but, more importantly, the reasons why they consume music in the first place. The motivations for listening to music are numerous and diverse (Schäfer et al., 2013; Lonsdale and North, 2011; Pridy et al., 2021; Villermet, 2021) ranging from mood regulation and identity formation to background ambience or active discovery, and these underlying intents fundamentally shape how users engage with recommendation systems. As such, any meaningful understanding of algorithmic influence must begin with an investigation into these personal motives and listening contexts.

2.2 The how and why users listen to music

As introduced, music discovery on streaming platforms is a deeply multifaceted experience, shaped by a range of individual and contextual factors. From the intent behind a session to the interface through which content is accessed, users engage with music in diverse and dynamic ways. As Raff et al. aptly put it, *"Music discovery presents itself in an instant and in a multitude of possible ways"* (2020, p. 476). This insight captures the everyday unpredictability of how people come across new music and the variety of approaches users adopt when interacting with streaming platforms.

2.2.1. Modes of Access and Their Impact on Listening Experience

One key factor that shapes this experience is the "mode of access" to music, as described by Villermet (2021, p.1). He defined that users can interact with streaming platforms through three primary modalities: organic access (self-selected songs), algorithmic guidance (automated recommendations), and editorial guidance (curated playlists or featured content). These "entry points" significantly influence the nature and the peculiarities of the listening experience.

In fact, each one of them tends to imply a different kind of listening: while algorithmic recommendations have been found to promote variety and exploration (at least to some degree), editorial playlists often prioritize popularity and commercial appeal, resulting in the so-called "filter niches". These "micro-music-environments" can lead to less diverse listening patterns, as they tend to favour more popular and mainstream artists, tending to demotivate exploratory behaviour. Moreover, typical "editorial-listeners" have been shown to prefer well-known and non-complex songs, with a tendency to follow familiar music choices (Ruth et. Al, 2016, p.75-76).

2.2.2. Individual Listening Styles: Typologies and Intentions

At the same time, the way a person engages with the platform, as to say their "individual style", adds another layer of complexity (Villermet et al., 2021, pag.5). Several researchers have attempted to categorise typologies of users based on differing criteria, such as listening goals, levels of control, or openness to discovery, in an attempt to capture this variability (Villermet et al., 2021; Raff et al., 2020; Ferwerda et al., 2017). Essentially, these frameworks are not merely classificatory but methodological: understanding both the intent behind a listening session (whether the user seeks familiarity, exploration, mood regulation, or background ambience) and the manner in which they approach the platform (passively letting music play, actively searching, curating playlists, or browsing editorial content) is essential prior to any analysis of how users experience algorithmic recommendations. Ultimately, they help us understand the motives behind listening. For instance, whether someone opens a streaming app to lift their mood, to focus, to socialise, or simply to fill the silence matters when we try to understand how recommendations are received and interpreted. These categorizations offer a truly valuable lens through which it is possible to understand the incredibly multifaceted use of music streaming platforms.

A useful starting point is to distinguish between different levels of activity or passivity in the listening experience. This distinction often hinges on where the discovery process begins, whether the user actively initiates a music choice or instead encounters music through external cues, such as algorithmic or editorial suggestions. Equally important is the degree of intention and control the listener brings to the session, which can vary greatly depending on their goals, mood, or context of use, especially if the focus is on music discovery (i.e. the implied degree of variety in one's listening habits).

To create this categorisation, Raff et al. (2020) firstly identified the motives for listening, mainly including mood management, interpersonal relationships, personal identity, surveillance and diversion and then concluded that users can mainly be categorised in four different categories of music discovery. Respectively active, semi-active, semi-passive and passive. What's especially relevant here is the user's varying degree of willingness to give up control to the algorithm (and the platform) in their listening session. Even if these can be grouped into broad typologies, the individuality of each listener remains central. This means there is no uniform interpretation to how users make sense of their experiences on music streaming platforms, as their listening is shaped by personal intent, context, and engagement style.

2.2.3. Personality Traits and Expertise: Their Influence on Music Discovery

In a complementary approach, Ferwerda et al. (2017) propose that personality traits can serve as a useful framework for modeling user behavior on music streaming platforms. Drawing on the Big Five personality traits (openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism) their study demonstrates that individual differences in personality are linked to varying preferences for music diversity. For instance, users high in openness to experience tend to seek out a broader range of musical content, reflecting a greater appreciation for novelty and exploration. Conversely, those with higher levels of conscientiousness may prefer more structured and predictable listening experiences. This personality-based model offers further insight into why user engagement with recommendation systems differs so widely: it reinforces the idea that personal dispositions fundamentally shape both the perception and reception of algorithmic suggestions.

Not only user inclinations and personality traits can have a direct impact on the listening experience, but also the degree of musical expertise tends to have an influence on how one approaches a listening session. It has been demonstrated that user expertise in a specific domain, which could be music, movies or any other form of art, affect the user interaction with recommended items (Bollen et al., 2010, 26-30). Hence, expertise is predicted to positively influence item attractiveness, meaning that users with higher domain expertise (in this case music) find recommended items more appealing, even if presented with complex recommendation sets. Moreover, users with higher musical knowledge tend to listen to more diverse music, both in terms of artists and genres (Ferwerda et al. 2016, 43-47).

2.2.4. Beyond Personal Preferences: The Social and Cultural Implications of Music Discovery

Taken together, these frameworks highlight the layered complexity behind how users engage with music streaming platforms. From motivational intent and personality traits to domain expertise, each dimension adds nuance to our understanding of listener behavior. But recognizing this complexity is not merely a call for deeper insight: it has direct implications for how we study culture, identity, and technology in contemporary life.

For sociologists of culture, media scholars, or researchers in digital humanities, this means acknowledging that algorithmic mediation is not a neutral process of distribution, but an active force in shaping taste, habits, and self-understanding. Music platforms have become everyday infrastructures of cultural consumption, influencing how people discover, relate to, and value music. By extension, it also allows us to understand how they construct their identities and social worlds. Failing to account for the interpretive and experiential dimensions of how users navigate these systems, the risk of flattening cultural consumption into a set of data points incurs, ignoring the ways in which users negotiate meaning, agency, and emotion within algorithmic environments.

Understanding this interplay is therefore not just about mapping complexity, but about confronting how cultural technologies structure everyday experience and how users push back, adapt, or internalize those structures. What's at stake is the ability to grasp how culture itself is being mediated, reshaped, and lived in digital spaces where choice and discovery are no longer solely human acts, but co-authored by systems we are only beginning to critically understand.

2.3 Role of human agency and diversity

User agency in music recommender systems has been widely debated. Some scholars argued that the influence of MRS can potentially be catastrophic, especially in the long run, reducing music diversity at both the individual and the market level, leading to feedback loops (i.e. the most popular items become increasingly dominant) (Mansouri et al., 2020), a visibility reduction of less popular content (Abdollahpouri et al, 2020), and an overall homogenization of the listeners taste (Hesmondhalgh et al., 2023).

It is most often remarked that algorithms tend to obscure niche content and rather promote the most popular artists. This not only affects the listeners' experience but also the ability or more niche musicians to reach an audience. Given that more than 120,000 songs are uploaded to music platforms daily, more than the entire output of 1989 (Ross, 2024), the competition for visibility is overwhelming. As Wang (2024, p. 3) points out, a significant number of tracks struggle to gain meaningful attention on streaming platforms. This suggests that, despite the apparent abundance of choice, the discoverability of new and diverse content remains limited.

This logically leads to the conclusion that, potentially, algorithmic recommendation systems may lead to taste homogenization. For instance, recommendation models can amplify existing popularity biases in the input data over time through self-reinforcing feedback loops, as MRS tend to focus more on popular items (Mansouri et al., 2020, p. 19-23). The concern here is not just about access but about how user tastes might be shaped, or reshaped, by this process.

Much of this debate has centered around the concept of "filter bubbles" (Pariser, 2012), with algorithmic filtering potentially creating a self-reinforcing loop, limiting users' exposure to diverse content and the potential for serendipitous discovery (Celma, 2010). Further research, affirmed that MRS may even personalize music consumption to the point of "isolating" it, reinforcing prior listening patterns and discouraging deviation from them (Anderson, 2020).

2.3.1. Beyond the Filter Bubble: "Filter Niches" and User Satisfaction

However, recent research suggests that this phenomenon may be more nuanced. Villermet et al. (2021) introduce the idea of "filter niches," in which users are not trapped in closed bubbles but are steered into narrower, commercially curated segments. These niches reflect commercial logics and can result in less exploratory behavior and reduced diversity. Nevertheless, it has been demonstrated that users are generally satisfied with their experience on music platforms and MRS and the claim that they may be overly restrictive is definitely layered and must be contextualized. In a study by Garcia-Gathright et al. (2018) among more than 18 thousands users, 81% reported a high overall satisfaction with personalized user recommendations. Since over-familiarity with recommendations can diminish listening enjoyment, and discovering unfamiliar songs is important for maintaining similar levels of pleasure (Gebauer, 2012, pp. 152–167), user satisfaction appears to require some degree of variety and diversity within recommendations.

2.3.2. User Agency: A Critical Factor in Shaping Music Discovery

Moreover, even if algorithmic recommendations have been proven to have at least a small influence on our listening habits, research grounded in user-centered approaches consistently finds that users themselves play the most significant role in shaping how these systems affect them, especially in terms of diversity and exploration.

Rather than assuming MRS directly cause homogenization, many studies now argue that human intervention is a decisive factor. For instance, in the case of algorithmically-generated playlists, research has shown that listening over time to world charts on the platforms has showed an increased diversity in users' listening behaviours (Bello & Garcia, 2021).

While recommender systems can indeed function as "technologies of control" (Gillespie, 2014; Anderson, 2015) that shape and constrain user behaviour, users cannot be considered as passive listeners devoid of agency.

It has been further demonstrated that "skipping is an overwhelmingly common behaviour" (Montecchi, 2020, p. 3), with approximately only half of the recommended songs listened from the beginning to the end. This suggests that listeners remain discerning and actively involved in curating their own experience. Similarly, another study (Beauscart, 2019) demonstrated that only 25% of plays in his sample originated from algorithmic suggestions and that tracks discovered on the 'smart radios' only lead to an average of four replays over the survey period. Furthermore, following recommendations does not necessarily imply passivity, as it could both be seen as a “novice’s practice as much as it could be the practice of an enlightened music lover who occasionally uses a digital tool to complete their exploration toolbox” (Beuscart, 2019, p. 25). Moreover, the degree of agency exercised by music recommendation systems is difficult to systematically measure and compare to that of users.

2.3.3. User Attitudes Toward Streaming Platforms: Beyond Content

Stepping briefly outside the platform itself, user attitudes toward music streaming are shaped not only by content but also by broader considerations: whether the experience is worth paying for, whether the platform is convenient, and whether it allows meaningful personalization (Barata & Coelho, 2021, p. 14). It has also been reported that music streaming platforms interfaces encourage a utilitarian approach to music, framing listening as primarily situational and functional and tailored to specific activities rather than identity work or aesthetic appreciation (Eriksson et al., 2018, p. 123). Nonetheless, users are not merely passive recipients of these frameworks: they actively navigate, reinterpret, and at times resist these algorithmically structured listening modes, demonstrating significant agency in shaping their musical experiences (Hemsondhalgh et al., 2024).

2.3.4. Algorithm Aversion: Mistrust and Skepticism

Even if strong claims about algorithmic control, reduced diversity, and homogenized taste have been challenged, another layer of concern remains: the skepticism and mistrust some users feel toward algorithmic systems. This phenomenon has been more generally defined as “algorithm aversion” (Castelo et al., 2019, p. 24-29) and it reflects user discomfort with opaque personalization, concerns over data use and a perceived loss of control (Eriksson et al., 2019). When the feeling of being pushed into pre-designed consumption patterns is felt, users tend to be suspicious and become disengaged in their listening activity (Katz, 2014).

Moreover, some users express dissatisfaction not only because of data practices or recommendation logic, but because algorithmic suggestions seem to lack authenticity.
As expressed by Chayka, “It’s easy to overlook the fact that when consuming content through digital platforms, what we see at a given moment is determined more directly by equations than such tastemakers. (…), there is no direct influence from editor, DJ, or booker, but, rather, a mathematical processing of crowdsourced data stretching to encompass every user on the site.” (2024, pag.57).

Besides, users also believe their taste cannot be reduced to a mere algorithmic modeling (Vlegels & Lievens, 2017). Further studies have also shown that manipulation perception is also fueled by a lack of knowledge and understanding about how the algorithms ultimately work (Komiak & Benbasat, 2006). Similarly, acquiring more knowledge about how they work increases the perceived level of control while using the platform, which ultimately improves user trust (Smith et al., 2022, p.4).

Because algorithms are often seen as lacking authenticity and conflicting with the personal and evolving nature of musical taste, many, but not all, listeners remain skeptical about their capacity to truly surprise them or create a deep emotional connection. Taste, as several users note, is cultivated over time through emotional, social, and contextual experiences that algorithms, reliant on quantifiable patterns, struggle to fully capture (Chayka, 2024, pag.57). As such, algorithmic recommendations may deliver efficient results but still fall short in reproducing the depth and complexity of human curation and discovery.

2.3.5. User Agency and the Mediation of Musical Taste

Ultimately, this skepticism towards algorithmic recommendations rests but rather on the individual analysis and interpretive stance of each user, shaped by their intentions and desires in using the platform and not on something universally identifiable or shared. While some listeners approach streaming services with an active orientation, seeking novelty, self-reflection, or depth, others may engage in more passive or habitual ways, accepting algorithmic outputs for their convenience. This variability underscores the importance of examining how users negotiate and make sense of algorithmic experiences in relation to their own evolving conceptions of taste, identity, and musical engagement.

Understanding music recommender systems is vital for cultural sociology because these algorithms shape what music is visible, popular, and valued, influencing how people form taste and identity. They are not neutral tools but active participants in cultural production, affecting diversity and inclusion by often favoring mainstream content. Ignoring this risks reducing culture to mere data, missing how users negotiate meaning and agency. Studying these systems reveals how culture is created and contested in the digital age, offering insights into power, representation, and social dynamics in modern cultural life. To fully grasp this, it is essential to view recommender systems not just as isolated technologies but as part of a complex network of human and non-human actors, a perspective explored through Actor-Network Theory.

2.4 A complex network

User-platform-algorithms relationships cannot be reduced to just three isolated "actors". According to Latour (1984), power is not something that one possesses. On the contrary, it emerges from the interactions within a network.
Therefore, claiming that either platforms or users have unilateral control or "power" over one another does not hold under this logic, as neither exerts control in isolation but instead influences each other reciprocally. Each actor is itself a network of many others (Bencherki, 2017) and each recommendation (or playlist/categorization) is the result of complex interactions among various human and non-human actors, including as far as developers, curators, algorithms and user data.

Actor-Network Theory further posits that non-human entities, such as algorithms, possess agency (Latour, 2005). In the specific context of music recommender systems, algorithms act as mediators and influence user choices to varying degrees, not only as passive tools, but as active participants helping to shape the listening experiences.

Moreover, an interesting perspective offered by ANT advances that since everyone acts in its own network, activity and passivity should not be fixed or strictly defined states but rather seen as effects or outcomes (Law, 1999, p.1-14). In fact, humans and non-humans are considered as equals (Nicolaus, 2019, p.7), which is crucial to erase the belief that algorithms are omniscient and all-knowing (Lee, 2018), both for researchers and users. Latour states "if an actor exerts power by having others perform actions for them, they do not actually possess power since it's others carrying out the actions" (1984, p.264); thus, it cannot be said that streaming platforms actually exert control, but only an influence on the listeners behaviour, which is then enacted and channeled through the actions of the user.

Technologies can also offer the so-called "affordances", defined as "actant" in ANT (Bewlett, & Hugo, 2016, 55-73), referring to the potential actions that arise from the relationships and negotiations between human and non-human entities. Within music streaming platforms, users can decide how to make use of them in unique and even unintended ways, mediating their role as listeners and curators alongside the algorithm and its recommendations. Agency is hence distributed and not harshly divided following some hidden power dynamic. Platforms delegate listening behavior to users, while users delegate taste curation, filtering it through personal judgment and context.

This framework challenges simplistic dichotomies favoring either platform or user, offering a rich lens to analyze these dynamics. Nevertheless, while ANT is valuable for understanding the structural and relational aspects of technological systems, it may need to be complemented with other theoretical approaches that foreground human subjectivity and emotional engagement to provide for a fuller understanding of user experiences.

2.5 Music Recommender Systems as "Technologies of the self"

Listening choices, what we decide to listen to, read, or wear, are deeply personal acts that reflect our changing moods and evolving sense of self (Chayka, 2024, p. 57).
Building upon this dynamic interplay, algorithmic tools have also been conceptualized as "technologies of the self" (DeNora, 1999; Karayakali et al., 2017), drawing on Michel Foucault's (1990a, 1990b, 1997b) notion of "practices of the self". These said practices entail complex assemblages that also have an ethical dimension, giving style and character ("ethos") to one's existence.

In this sense, users never entirely lose their autonomy; on the contrary, the influence that an algorithm can produce on users is continuously constructed thanks to an "ongoing negotiation" between the user agency and algorithmic suggestion (Karayakali, 2017, p. 35(2)).
Users actively modify their listening habits, using platforms as "ethical substances" to cultivate diversity in their music tastes and engage in continual self-transformation (Karayakali, 2017). This dynamic aligns with a broader cultural imperative to "transform yourself" (Sandywell & Beer, 2005).

In addition, music preferences has even been linked with personal characteristics as far as self-esteem: for example, young people with low-membership self-esteem are more likely to be attracted to "intense/rebellious" musical styles, such as hard rock, heavy metal and punk, while a preference for "energetic/rhythmic" music was positively related to the respondents' membership self-esteem (Clark & Lonsdale, 2023, pag.1125-1226). Shared musical experiences have further strengthened social bonds and enhanced emotional health across diverse cultural contexts (Bogt et al., 2014). Taste has even been described as a "fundamental part of the self," where developing one's musical sensibility contributes to constructing a firmer sense of identity (Chayka, 2024). In this context, music recommender systems not only suggest songs but also invite users to reflect on and modify their listening patterns, participating in ongoing processes of self-transformation (Karayakali et al., 2017).

Finally, framing music recommender systems as "technologies of the self" brings to light how listening is not just consumption but an active, ongoing process of self-expression and transformation. This approach challenges simplistic ideas of algorithmic control by emphasizing the fluid, negotiated relationship between users and recommendations, where music becomes intertwined with identity and ethical reflection. For researchers, this means moving beyond algorithm-centric analyses to consider the broader human and cultural contexts shaping musical engagement. Understanding this interplay is essential for developing systems that support meaningful, diverse, and personally relevant listening experiences. With this foundation, the next section will focus on defining music recommender systems themselves, exploring their structures and functions that underpin these complex interactions.

2.6 Defining Music Recommender Systems

Firstly, it is essential to define music streaming platforms and MRS. Music streaming platforms are nowadays widely used as one of the main means to stream music online (and potentially offline) and were created as music digital libraries, constructed to keep the user longer on the platform (Villermet, 2021). Since the first major commercial music recommendation system was launched by Pandora in 2000 with the "Music Genome System", with its manual categorization system based on up to 450 musical characteristics analyzed by trained musicologists, (Schmidt & Migneco, 2010) and a pairing of songs based on the similarity of their "genes" (i.e. shared musical traits) (Joyce, 2006), MRS have evolved significantly.

Music recommender systems are defined as software tools and algorithms designed to suggest items that are most interesting to a user (Adiyansjah, 2019, 101), "guiding him in a personalized way to interesting (..) objects in a large space of possible options" (Burke, 2002, p. 331-370), in order to achieve consumers' satisfaction (Karayakali et al., 2017). Streaming platforms typically employ MRS based on various recommendation techniques.

2.6.1 Collaborative Filtering vs Content-Based Recommendations

The most widely used approach is 'collaborative filtering', which recommends songs that other consumers with a similar profile to the user have also liked (Beuscart et al, 2019). This method relies on either implicit feedback, such as streaming activity logs, or explicit feedback, like user-curated collections (Matrosova et al, 2024).

Another widely used technique is content-based recommendations, which identifies specific items' features, like audio features or social tags, that a user is likely to respond positively to. While indeed very effective, these approaches are not without limitations and they have been harshly criticised as they may possibly lead to incorrect and predictable recommendations.

For instance, content-based recommendation systems can suffer from over-specialization, as only a limited set of items can be recommended to the user, the ones that have something in common with what the user has already listened to or demonstrated to like (Iaquinta,2008), creating the so called "serendipity problem" (Gup, 1997, A52). In fact, too similar items to what the user has already seen should not be recommended, as in theory this would not be effective and liked by the user. Furthermore, following the study of Celma and Cano (2008), given a very popular artist, the probability of reaching a similar artist in the *long tail,* meaning the portion with lesser-known artists who receive significantly fewer streams, is essentially zero. Not only the algorithm tries to play songs in the same "portion" but also the artists in the "head" (the most popular ones) are only 82 out of almost the 300,000 taken into analysis, while the majority sits in the mid and only 1% in the tail (Celma & Cano, 2008). Furthermore, not only do content-based MRS tend to suggest the more streamed artists, but also expert-based recommendations tend to ignore the tail portion, making it almost impossible to discover niche artists.

Also, content-based (CB) recommendations are mostly based on acoustic properties and it has been demonstrated that acoustic properties relevant to music perception are largely subjective (Schedl et al, 2018, p.99). Therefore, CB approaches without personalization struggle to achieve true effectiveness, so it is essential for an MRS to be effective and efficient to incorporate user-specific feature-based similarity models, comparing how much a musical feature in an item matters for a specific type of user rather than the feature per se. This will also be addressed later on.

On the other hand, collaborative filtering (CF), which is memory-based and relies on identifying a user's 'nearest neighbour', (i.e. the closest most similar user) (Song et al., 2012), struggles to recommend newly released or less popular items due to insufficient usage data. Also in this case, popularity has a strong effect on the generated recommendations, as it was proved that "CF tends to reinforce popular artists at the expense of less known musicians" (Celma and Cano, 2008, p.7) and there is a strong correlation between an artist total playcounts and the total playcount of similar artists in the algorithm recommendation process.

2.6.2 Limitations of the algorithms and biases

This limitations makes it particularly difficult for niche content to gain visibility (Dieleman & Schrauwen, 2013) and have thus been criticized for fostering an environment "*where only the successful get more successful"*, a phenomenon known as the *Matthew effect* (Hesmondhalgh, 2023, p. 25). Therefore niche markets are not exploited to its fullest, as even if niche contents are available, streaming platforms and their recommender systems do not necessarily help the users in finding them (Anderson, 2020).
Alongside this popularity/discoverability bias, other biases, such as the demographic bias, which reveals a strong mismatch between male and female recommendations (Pelly, 2018; Eriksson & Johansson, 2017), further support the argument that streaming platforms and MRS tend to flatten variety (Anderson, 2020) and ultimately serve market interests (Hodgson, 2021).

Building on this perspective, recommender systems would just reflect back to us "categorical images of our self" (Prey, 2018, p. 1094), failing to leverage the archival infinity of the platform and pushing toward more functional, background music consumption rather than active, engaged listening. Nevertheless, it has been proven by further research that, when put in comparison with other modes of recommendations like editorial/expert recommendations, algorithmic recommendation-based access modes favour less popular items (Villermet, p.11, 2021). This would mean that MRS do not necessarily limit one's own musical variety during listening sessions over time. Instead, it would be more appropriate to state that there is "no blanket answer to the intertwinement of recommendation use and consumption diversity" (Villermet, p.1, 2021).

Critically, to assess the true influence of MRS on listening habits, one must consider the listening session's goal, as to say whether users want to play new music passively, explore actively, or curate for future listening (Garcia-Gathright, 2018). Satisfaction with recommendations correlates strongly with achieving these goals.

Furthermore, both users and scholars have described MRS as "magical" in their ability to transform users' thoughts into actions (Finn, 2017; Hodgson, 2021). This effect contributes to the perception of algorithmic recommendations as authoritative and even unquestionable, leading some users to interpret them as "*the word of God"* (Gillespie, 2014). As a result, MRS are often seen as omniscient when in reality their functioning, however opaque it may seem, relies entirely on user-provided data. Also, these systems continuously react to user activity, by generating a new set of recommendations, that not only shapes their listening activity but also accompanies them in an ongoing self-transformation process (Karayakali et al., 2017).

Therefore, MRS without human activity would be void of any meaning. Moreover, their activity is strictly tied to the recollection of data, without which it would be completely void and incapable of generating recommendations.
Listening to music is an activity that is conditioned by many different factors, that cannot only be reduced to an omniscience that directs the user to a certain type of items: apart from the characteristics of the situation itself, like social surrounding, the place and weather conditions, also the personality, emotional state of the listeners and their activity in the moment (Schedl et al. 2018), play a crucial role in determining what the user will listen to and what items he desires to consume in that specific situation.
A situational aware MRS would be incredibly effective in detecting and accounting for all the factors that have an influence on the musical choice of the listeners, but it is not easy to employ and integrate a variety of situational signals (including the emotional state of the user, the personality of the users, weather, context, etc.) on a very large scale (Schedl, 2018; DeNora, 1999**).** Not only is it difficult to implement such systems reliably across millions of users, but it also raises significant concerns about user privacy, consent, and the potential for intrusive surveillance. In this sense, pursuing deeper personalization risks crossing ethical lines, where the cost of improved recommendations may come at the expense of users' autonomy and data security.

2.7. Beyond the Algorithm: Everyday Engagement and User Experience

While a substantial body of literature has explored Music Recommender Systems (MRS), existing studies predominantly rely on quantitative data such as user activity logs, play counts, algorithmic output, and consumption patterns. Researchers also analyzed the flaws of these algorithmic systems, focusing on critiques around user passivity and filter bubbles among many, or on attempted classifications of user groups. These metrics, while valuable for understanding broad patterns of usage, fall short when it comes to capturing subjective experiences of individual users.

In this context, one consistent theme that emerges is the crucial role of the user's perspective in order to truly understand how MRS (and music streaming platforms) are situated in everyday listening habits. Users, in fact, do not use these tools in a passive way. Rather, they actively interpret, negotiate and even resists these mediated experiences in varied and complex ways.

Therefore, this study focuses on the question: *How do music streaming users make sense of and engage with recommendation systems in their listening habits?*

This broad inquiry covers users' listening behaviours, how they interpret and relate to music as part of their identity, what they feel is represented or omitted by the platform, and how they manage the concerns and opportunities presented by platforms and recommendations. In doing so, it addresses a gap in the literature by shifting the focus from algorithmic output to user interpretation and lived experience. In this respect, this study aims to analyse what these dynamics mean to users on a personal level and how the mediation with said technologies potentially shapes their listening habits.

Consequently, the intricate dynamics of human and non-human mediation cannot be fully understood through quantitative data alone. As such, this study employs a qualitative method, starting from 14 semi-structured interviews that informed an inductive thematic analysis. By gathering in-depth, personal accounts from users, this research can shed light on the meanings they ascribe to their experiences with MRS. This ultimately has important implications both for further research and for the development of more inclusive and informed music recommendation systems.

In contrast to the reductionist view of music as just data points for consumption, this study emphasizes the importance of subjective, emotional, and social factors in shaping music consumption patterns. By examining how users navigate and reinterpret recommender systems, it seeks to unravel the unspoken dynamics that often go unnoticed by traditional data-driven approaches. This research is not just about identifying patterns; it's about understanding how algorithms intersect with the human experience, how they both constrain and expand the possibilities of music discovery. In doing so, it aims to disrupt prevailing assumptions and spark a broader conversation about the future of digital platforms as spaces for personal expression rather than just consumption.

3. Methods and Data

This study employs a qualitative research design using semi-structured interviews, as briefly introduced before, analysed through thematic analysis (Braun & Clarke, 2006). Given the main research question, “How do music streaming users make sense of and engage with recommendation systems in their listening habits?”, a qualitative research design is particularly appropriate. In fact, the ultimate goal of this research is to investigate in-depth the users perception of their experience on music platforms. This method allows for an in-depth exploration of subjective experiences and perceptions. It also examines the diverse ways in which users negotiate their role as listeners and assert their agency within streaming platforms and music recommendation systems (MRS).

This approach focuses on the users themselves, addressing a notable gap in the literature, which often prioritizes algorithmic functioning over “real-life” users experiences. Also, this research does not focus on the “what” they consume, but instead the “how” and the “why”, addressing users modes of consumption, their reasons to do listen to music, how they make use of music streaming platforms in their daily life, and their thoughts and feelings about them. For instance, qualitative methods are especially effective when the goal is to understand complex phenomena (Creswell, 2013; Patton, 2002) where individual meanings are central to grasping the true, and often hidden, dynamics of the topic.
An inductive approach guides this research, without the goal of testing an initial hypothesis, allowing for relevant themes and insights to emerge directly from the participants’ perspectives, given the subjective and experience-based nature of this topic and, ultimately, this research.

Semi-structured interviews were selected as the data collection method to balance a consistent set of core questions, with the flexibility to explore the themes emerging in the interviews (Adams, 2015). Besides, this method allows for following a set of guiding questions while remaining responsive to the interviewee’s unique perspective, avoiding repetitive questions and a tailored in-depth exploration of diverse matters (Brinkmann, 2013). In this case, it was crucial to ensure that participants could reflect on their habits, feelings, and perceptions. At the same time, they needed to feel free to explore any discourse relevant to the study, allowing for valuable insights into how each user experiences streaming platform services. Thereafter, this method aligns with the ultimate goal of understanding how individual users subjectively make sense of algorithmic systems embedded in their everyday consumption.

Thematic analysis was also very suitable for the aim of this research, guaranteeing the possibility to identify and explore patterns with qualitative data (Braun & Clarke, 2006), like in this case with interview transcripts. Furthermore, it helps in understanding how participants make sense of complex experiences, such as their interactions with algorithmically driven music recommendation systems. Moreover, it enables the identification of both explicit and latent themes. Additionally, it allows for the registration of recurrent themes across interviews, as well as highlighting the differences and similarities in how individuals interpret and engage with MRS. Such comparative insight is essential both for understanding the diversity of user experiences and the identification of shared interpretative frameworks. On top of that, thematic analysis makes it possible to ensure transparency and coherence in the analytical process, making it possible to balance the subjective nature of the research.

3.1 Data Collection and Operationalization

To collect data a total of 14 interviews were conducted either in Italian or English with self-identified music lovers, who regularly use music streaming platforms. Interviews lasted 45 minutes on average and they were conducted either in person or via phone call, based on the preferred mode and availability of the participant. The interviews were audio-recorded with the participants' consent, to ensure accuracy and facilitate later transcription and analysis.

Participants were selected based on their high engagement with music, particularly music streaming platforms, which, for the purpose of this research, refers to frequent or, most often, daily use. This choice was made because participants possess extensive music knowledge and, given their daily engagement with music, are likely to have a deeper understanding of their preferences, as well as a heightened awareness of what they like and dislike about MRS and their overall music listening habits. Compared to casual users, these participants are more likely to have developed established routines, clear preferences, and a critical awareness of both the affordances and limitations of recommendation algorithms.

Finally, the interview guide was designed to encourage an open-ended exploration of participants' experiences with music streaming platforms. Since this study adopts an inductive approach, general concepts from the literature, such as user autonomy, algorithmic influence, and discovery, were used to shape open-ended questions. However, these concepts served only as flexible entry points, not rigid categories, acting as "sensitizing concepts" (Charmaz, 2003) to inform the research. The interviews always remained open and conversational, with persistent follow-up questions tailored to the participants' responses and unique experiences.

3.2 Sample and Data Selection

The goal for this research was to combine online purposive sampling, reaching music lovers on groups of target forums on Discord, Reddit, Facebook and Spotify Community, and purposive-snowball sampling, aiming to reach users with a clear interest for music and music digital platforms (Patton, 2002). Unfortunately, the initial attempt to recruit participants on forums was unsuccessful, and it was not possible to finalize due to time constraints and a lack of response from the targeted groups. As well, this may have been influenced by the voluntary nature of participation and the absence of incentives. As a result, the recruitment strategy shifted to personal networks.

In the end, the sample was selected initially with purposive sampling through personal contacts and then expanded through snowball sampling (Noy, 2008), always targeting individuals with high engagement in music streaming practices. This method proved especially useful for reaching participants outside my immediate network, involving people who not only love the practice of listening to music, but also work with music or have it as their main hobby or passion.

The final sample consisted of 14 participants (66.7% working adults and young adults; 33.3% students), diverse in terms of age (from 20 to 58 years old), gender, overall background, and musical preferences (see Table 1). As previously mentioned, the primary focus of the sample selection for this research was to identify music enthusiasts who possess a certain level of musical depth, knowledge, and, in some cases, even expertise. This was particularly important once the research topic had been defined.

The ideal participants, in my view, are individuals who not only engage with music on a deep level but also reflect critically on their listening habits and experiences. Research suggests that those with higher musical training or interest are more likely to engage analytically with music (Colley, 2008, 2038-2055; Cohen et al., 2006). Given that the interview guide was designed to be introspective and analytical, exploring aspects of personal identity, I believed that selecting individuals with a deeper connection to music would enrich the research. Such participants were likely to provide well-formulated and reflective insights, offering valuable perspectives on music recommendation systems and music streaming platforms more broadly.

Participant	Name	Age	Nationality	Gender	Education	Occupation	Music Involvement
1	Alessia	20	Italian	Female	High School Degree	Student/Dancer	Professional Dancer and Music Enthusiast
2	Bob	24	Swedish	Male	High School Degree	Music Producer/Boat Driver	Music Producer/Singer
3	Carlo	55	Italian	Male	High School Degree	Worker	Music Lover
4	Davide	27	Italian	Male	High School Degree	Electrician	Music and Concerts Enthusiast
5	Johan	23	Swedish	Male	High School Degree	Worker	Music and Concerts Enthusiast
6	Lucrezia	25	Italian	Female	Law Degree	Student	Music and Concerts Enthusiast
7	Marco	28	Italian	Male	High School Degree	Professional DJ/ Event Organizer/3D Printer Operator	Professional DJ/Vinyl Collector
8	Matteo	22	Italian	Male	Bachelor Degree	City Administration Employee	Music Lover
9	Nicola	24	Italian	Male	High School Degree	Storekeeper	Amateur Rapper/Music Enthusiast
10	Nadia	24	Italian	Female	Bachelor Degree	Student/Babysitter	Amateur DJ/Music Lover
11	Philip	58	Swedish	Male	Law Degree	Lawyer/Boat Captain	Professional Singer and Producer/ Record Collector/ Music Connesseur
12	Pietro	28	Italian	Male	PhD	Engineer	DJ/ Music and Concerts Lover
13	Rolf	24	Swedish	Male	High School Degree	Boat Captain	Amateur Rapper/ Music Enthusiast

14	Stella	23	Italian	Female	Master's Degree	Waitress	Amateur Singer and Musician/Music Enthusiast/ Amateur DJ

Table 1: Participants' attributes

Nevertheless, this research focused on a specific target group, which may not be universally representative and could be considered relatively homogeneous. In addition to this, the voluntary nature of participation and the absence of incentives may have contributed to a self-selection bias, where individuals who chose to participate were more motivated and personally invested in music and streaming platforms than average users. Furthermore, the absence of incentives may have demotivated users from music forums and online communities to participate, not allowing for a more randomized sample. Since recruitment initially began through personal contacts, the sample may also reflect a degree of homogeneity in terms of engagement with music, also considering that individuals were later selected through snowball sampling, therefore by referral from peers with potentially similar interests or profiles, narrowing the diversity of perspectives.

However, the insights generated still hold significant value within the broader literature on music streaming platforms and music recommendation systems (MRSs), as they offer rich, in-depth perspectives grounded in participants' personal engagement with music. The added element of participants' intrinsic interest in music contributes to the depth and reflexivity of their reflections. The aim of this study is not to produce statistically generalizable results, but rather to generate rich, in-depth insights into how individuals interpret and negotiate music recommendation systems. Future research could expand this scope by exploring how music novices, casual listeners or new users of streaming platforms make sense of algorithmic recommendations and negotiate their listening experiences in different ways.

3.3 Data Analysis

The analysis followed an inductive thematic approach, allowing themes to develop directly from the interview material without applying predefined categories. All interviews were transcribed verbatim, capturing the exact words and expressions used by participants. This step supported a deep familiarity with the data and helped preserve the tone and rhythm of participants' narratives, which proved valuable when identifying subtle patterns in their descriptions of listening practices.

To begin, transcripts were carefully read and annotated with preliminary notes on recurring topics, significant expressions, and emotionally charged responses. These early observations helped to form initial codes, short descriptive labels that captured key ideas, such as "skipping recommendations," "algorithm gets me," or "playlist as identity." Rather than focusing on frequency alone, particular attention was given to the meaning and context of these expressions, recognizing that a single, well-articulated account could open up a broader theme. All transcripts were analyzed in their original language (i.e., Italian or English) to maintain the meaning as intact as possible and to avoid losing any details during translation. The codes (and themes) were subsequently translated into English for the analysis, ensuring accuracy and preserving the integrity of the data.

As coding progressed, similar codes were grouped together and gradually shaped into more abstract themes. These themes reflected common ways in which participants talked about their experiences with music streaming platforms, especially around issues of control, discovery, identity, and emotional connection. Patterns were not forced into uniform categories; instead, contrasting or even contradictory perspectives were included, as they highlighted how users negotiate their roles in relation to algorithmic systems.

To keep the analysis grounded, each theme was checked against multiple transcripts, ensuring that it represented a consistent pattern rather than a one-off comment. Notes taken during coding sessions helped track how and why certain themes evolved, making the reasoning behind analytical decisions transparent. For example, a theme on “algorithmic surprise” emerged from a mix of excitement and discomfort expressed across several interviews, showing how users interpret recommendation outcomes both as a tool and as a disruption.

After identifying the main themes, they were connected back to the broader research interest in how users interpret and make sense of algorithmic recommendations. Although the process remained inductive, many of the emergent themes echoed key concerns in the literature, such as user autonomy, musical identity, and the tension between personalization and predictability. Throughout the analysis, care was taken to reflect on the researcher’s positionality and potential biases, especially considering a shared familiarity with the platforms and practices discussed. By staying close to participants’ language and perspectives, the analysis aimed to remain faithful to the lived experience of music streaming, while also offering structured insights that could contribute meaningfully to ongoing academic discussions.

In the following section, I will discuss five final themes that emerged from the analysis, focusing on how users navigate their relationship with recommendation systems and the impact of these systems on their listening habits and identities.

4. Analysis and Results

This thematic analysis explores how 14 music listeners with diverse backgrounds engage with music streaming platforms (MSP) and music recommendation systems (MRS). Participants vary in age, musical taste, and relationship with music, including DJs, musicians, and everyday listeners. The analysis highlights shared patterns and differences, focusing on usage habits, discovery mechanisms, emotional connection, algorithmic influence, and the role of agency in shaping musical experience. 5 main themes were observed: Mood Regulation and Emotional Engagement; Algorithmic Influence on Discovery and Diversity; Perceived Agency and Control; Taste and Musical Identity; Platform Perceptions and Critiques.

4.1 Mood Regulation and Emotional Engagement

Across the interviews, it is evident that music serves as an incredibly powerful and useful tool for emotional regulation. Users generally select the songs and genres that align with or can potentially alter their emotional state, based on the situation. Participants in the study highlighted how their mood played a central role in shaping their music choices, using music as a way to navigate different emotional landscapes. Music therefore results as deeply intertwined with emotional management, allowing the listeners to exert an influence on their mood and emotions through music (DeNora, 1999).

For many participants, music was a true experience, not just about enjoyment, but most and foremost about finding the right *emotional habitat* to match their psychological state. For instance, Elena, an amateur musician and music lover, articulated that she adjusts her listening according to her mood, indicating an active process of “resetting”, “depending on the moment”. Music results as an incredibly handy resource to serve emotional and psychological needs, being part of a dynamic process of self-expression (Chayka, 2024). Approximately 90% (13/14) of the respondents expressed this, emphasizing also that music can help to focus, “to relax after a stressful day” (Alessia, Participant 1, professional dancer) or can help “when I need energy” (Nadia, Participant 10, aspiring DJ). These consistent statements demonstrate that mood management is not just a side effect of listening, it is one of the primary drivers of platform engagement and music selection.

Mood management therefore results as the primary motive to both discover and consume music among the participants. Music choice is often based on what the respondents feel, as Lars (music lover and *connoisseur),* pointed out:” Maybe I wake up with a song in my head, then I will play or listen to that genre at least” (Rolf, Participant 13, music lover). Furthermore, many respondents highlighted that the emotional regulation function of music is further reinforced by the fact that they can listen to music anytime and everywhere, accompanying them across mood swings and situational changes. According to the interviews, mood could either be enhanced ("Mood enhancement") or regulated ("emotional regulation").

Interestingly, several participants described an active engagement with music aimed specifically at regulating their feelings during distinct moments. Matteo (Participant 8) explained that they often "choose energetic music when I need motivation" but prefer "softer songs to calm down" and especially when listening to music alone, to exercise music's full potential emotional power.

All the participants consistently described music as a vital tool to manage their emotional states and navigate daily life, in every situation and context. Many interviewees explicitly framed music as a means for "mood enhancement" and "emotional regulation", underscoring the affective power music holds in their everyday routines. For example, Lucia, a professional dancer, stated that they use music "to relax after a stressful day" and as a "way to escape from real-life problems". Similarly, Matteo (Participant 8, professional DJ) shared "(music) helps me to escape from negative thoughts," highlighting music's role as a form of emotional diversion. These personal testimonies resonate with Raff et al. (2020), who identify mood management as a primary motive in music discovery and consumption, emphasizing that listeners often seek music that aligns with or shifts their emotional states.

This function is further emphasized by the fact that music streaming platforms (MSP) allow them to bring music everywhere and anytime, bringing music's emotional and personal value in any situation. As Matteo (music lover, participant 8) said: "For me listening to music when you want has a personal meaning, intimate and therapeutic, and I can do it wherever, so it is amazing". The ubiquity and mobility of streaming platforms deepen the emotional bond listeners form with music, making mood-responsive listening a seamless part of daily life.

Music is therefore inextricably tied to emotions, demonstrating how ingrained music is in the regulation of our moods and even operates on an unconscious level. In fact, many times the choice of music is impulsive, connected to a specific situation and emotionally and sensitively caused (Karayakali et al., 2017). Moreover, music is not only used to enhance a specific moment and accompany it in a complementary way, but it was also reported to be extremely important as an escape mechanism (Philip, Participant 11, professional musician and producer). Music as a form of escapism was observed in 70% of the participants, turning it into a form of respite from daily pressures.

The emotional connections formed through music also extended to moments of nostalgia and reflection. Johan (Participant 5, Music enthusiast) mentioned how "certain songs bring back memories and make me feel connected to past experiences," illustrating music's capacity to evoke personal history and emotional depth, evoking positive, negative or even embarrassing moments. This use of music as a bridge to one's past or as a companion during introspection also reflects DeNora's (1999) concept of music as a technology of the self, where listening becomes an intimate practice shaping mood and identity. This emotional engagement with music reveals a broader pattern of strongly purpose-driven listening, where music is not just a background element, but a true intentional choice to affect and shape one's emotions.

Nevertheless, several participants highlighted that music also matter in its more passive form, with the main scenario being described in this case as being in a social environment. In this scenario, participants have declared that music is used as a unifying background element, also usually corresponding to more positive/higher tempo songs. This dynamic and intentional use of music aligns with the findings of Ferwerda et al. (2017), which suggest that users' listening goals often shift based on their current emotional needs and contexts, reinforcing that the purpose of music consumption is far from static and evolves continuously, even momentarily, with some participants affirming that the algorithm cannot really keep up with their mood changes.

The data also reveal a complex relationship between emotional engagement and listening behavior. Some interviewees preferred to let the algorithm select tracks passively when in a relaxed or distracted state, while others took control by curating playlists or skipping songs to better match their mood (Codes: Active vs. passive listening; Skipping songs). Alessia (Participant 1) remarked, "Sometimes I just hit play on my Discover Weekly and let it surprise me, but other times I am very picky about what fits my mood." This duality demonstrates the fluctuating degree of agency users feel when regulating emotions through music, a theme further explored under perceived control.

Moreover, the concept of music as an "escape" was recurrent, where participants described immersive listening as a way to detach from stress or external pressures. Music, in fact, is not only used to regulate emotions but also to escape from reality". Participant 9 articulated this by saying, "When I feel overwhelmed, music is my safe place; it blocks out everything else." Such immersive experiences align with Chayka (2024), who highlights music's role in fostering personal sensibilities and providing emotional refuge, situating listening as a form of self-care and emotional resilience.

In sum, this theme reveals that users do not merely consume music as background noise or for passive entertainment; rather, they engage with it in deeply personal and emotionally charged ways. Music becomes a tool to modulate feelings, recall memories, and create a safe psychological space, demonstrating that mood regulation and emotional engagement are fundamental to understanding user interactions with streaming platforms. This aligns with the literature's broader recognition that music listening is an active, context-dependent practice intimately linked to human emotion and identity formation.

4.2 Algorithmic Influence on Discovery and Diversity

Another centrla theme that emerged from the interviews was the way users navigate and experience music discovery through algorithmic recommendation systems. Algorithmic suggestions were a constant feature in the participants' described listening sessions, but how users experienced and interpreted these recommendations varied significantly. Furthermore, the critiques about MRS ranged from repetitiveness issues (i.e. frequently receiving the same recommendations), algorithmic limitations and possible biases, evident even to the users.

First, 85% of the participants (12 out of 14) declared that MRS had a significant impact on their music discovery habits. What this shows is that when users interact with an instrument as inherently interactive as algorithms, listening habits and routines, taste and even identity are potentially influenced. Algorithms therefore come to light not as passive suggestion-generating tools, but as active constructors of the users habits on the platforms, and consequently their listening preferences.

Many participants acknowledged the positive role MRS and music platforms themselves occupied in the expansion of their musical horizons, especially in the initial periods of usage. Stella (Participant 14), for example, stated: "MRS has shaped my taste by proposing new artists… but now that I listen to a lot of different genres, I do not feel supported in the discovery of new music anymore." This comment in particular represents the initial perception that users have of algorithms as powerful agents and convenient platforms that can allow them to listen to an infinite catalogue of musical items. Nevertheless, when one acquires his own predisposition towards music discovery, it's not the ultimate cause of discovery is the algorithm alone: rather, it becomes an "ally", as described by more than half of the participants, helping them in finding new songs.

Therefore, with time, MRS can also present themselves as inapt for the users and not aligned with their musical interests. As Nadia (Participant 10) reported, she found a lot of songs that surprised her, but she felt stuck in “a loop of similar suggestions”. This was pointed out by more ten participants, reflecting the so-called “filter bubble” problem. It is commonly associated with algorithmic suggestion systems, due to their inherent functioning based on trying to assess and provide content that the user may like (Pariser, 2011; Schedl et al. 2018). In this limiting scheme, algorithms reinforce prior preferences, limiting serendipitous discovery of diverse music. Given the frequency with which it has been reported, it seems to be a widely shared concern.

One user (Luca, Participant 12), for instance, decided to try to train the algorithm, adopting a proactive behaviour towards MRS, attempting to direct it to items that were more similar to what he actually liked to attempt to deviate the regular functioning of MRS. This further enhances the fact that users do not ever surrender completely to the algorithm. Instead they negotiate with it, exerting additional control by curating their playlists, liking or skipping songs or even switching platform if they are extremely dissatisfied with its functioning.

Despite widespread critiques, users also recognized that without music streaming platforms (MSP) and MRS it would have been incredibly hard to find unknown genres that they now love, especially during earlier stages of their musical engagement. Rolf (Participant 13) commented, “Without Spotify, there wouldn’t be as many genres out in the world… but sometimes the recommendations are way off track.”

This highlights an issue that seemed to be particularly prevalent in this research sample, potentially due to the participants’ high engagement and/or expertise regarding music; while tools like Spotify’s Discover Weekly or Release Radar (Codes: Platform suggestions; Daily Mix / Discover Weekly) are specifically made to allow users to discover new music more easily, they often fail to consistently accommodate evolving and more specialized tastes and music profiles. Here rests the paradox of algorithmic discovery, offering everything but frequently failing in navigating efficiently the “long tail” of music catalogues (i.e. the section with less popular/niche artists) (Celma and Cano, 2008).

In addition, 64% of the participants (9 out of 14) mentioned a desire to discover less mainstream music or underground artists on MSP, turning to other sources in order to find music that satisfies their need for more “unique” musical items. Some declared that they usually get better suggestions from talking to friends (Nadia, Participant 10), from real-life experience or browsing on online playlists, as the most used MSPs tend to offer items that are already familiar to the user.

MRS and MSP, therefore, stumble upon the difficulty of truly grasping the desires and peculiarities of the users, tending to reinforce known patterns rather than encouraging transformation. Nevertheless, the interviewees never demonstrated a passivity towards this mechanism and, if unhappy with the content proposed by MRS, they would just find another way to fulfill their aspirations for musical diversity. Ultimately, they demonstrated practically the Foucauldian idea of ethical self-practice, reshaping their taste actively while resisting externally imposed limits, if present.

Moreover, many users from this study's sample reported that it is hard to comprehend why they get some recommendations, which also affects users' trust and potentially even their engagement with the platform. Luca (Participant 12) described the algorithm as "probabilistic" and "influenced by mass preferences rather than his own personal taste", contributing to doubts about how personal and tailored the recommendations actually are. Yet, it's important to note that not all users reported negative feedback. Magnus (Participant 11), for example, appreciated the passive ease of algorithmic discovery, admitting that he loved to possess a tool able to find music for him. In this case, the primary function for which algorithms were created, as to say to easen the burden of manual selection, seems to be particularly satisfied.

In conclusion, the insights from participants reveal a complex, evolving relationship with music recommendation systems. While these systems undeniably play a key role in broadening users' musical horizons, especially in the early stages, they also expose limitations that become more evident over time. The importance of the algorithmic suggestions paradox lies in the fact that music discovery is deeply tied to identity and autonomy and that users must thus be able to negotiate their preferences with the platforms. Listening becomes less about convenience and more about crafting a distinctive auditory identity.

4.3 Perceived Agency and Control

Building on the previous findings, another notable theme that emerged was the varying degree of control participants feel when interacting with music recommendation systems. Mostly, frustration surfaced when users perceived that MRS were trying to seemingly orient, and to some extent control, their listening session. A complex negotiation of autonomy in the users' listening practice on MSP therefore results apparent.

4.3.1. User autonomy: Active vs Passive listening and the Desire for Control

A striking finding was that 70% of the participants (10 out of 14) actively curated their playlists and adjusted their listening habits in order to maintain control over the recommendations received by the system. A recurrent behavior consisted in skipping songs that either didn't fit the user's profile or the context or mood in which it was suggested (Codes: Playlist creation; Skipping songs; Choosing vs. following suggestions). Even if "bad" suggestions can feel annoying, users still "feel in charge of their listening session", as they can decide how to react to it (Johan, Participant 5). Moreover, users also reported that exercising control and being "active" in their auditory session on MSP causes a sort of self-fulfillment, bringing satisfaction if the chosen song "hits as it should, at the right moment" (Lucrezia, Participant 6).

Exercising agency is also a way to escape from the filter bubbles users often fall into. Nonetheless, participants also shared that they appreciate the possibility of letting the algorithm pick the next songs, especially when they do not have something specific in mind or while they are doing another activity. For instance, while they are relaxed or distracted, but still want to listen to music, the algorithm becomes a convenient tool; if not, if they seek a more tailored and personal experience they can take control of it. This balance of agency is critical to understanding user satisfaction with MRS. While users enjoy the convenience, they also express a strong desire to curate their experience, often adjusting or bypassing the algorithm to better reflect their mood or identity.

4.3.2. Empowerment vs Manipulation

Despite the control users often exercise, many of the interviewees also voiced concerns about being subtly "manipulated by the algorithm". Pietro (Participant 12) noted that after receiving suggestions of songs he did not like, repeatedly, he felt like the algorithm was trying to push him in a direction he didn't fully agree with. Yet, the desire for greater control means that users actively resist said manipulations by bypassing or rejecting certain suggestions. 50% of participants (7 out of 14) reported to deliberately seeking music outside the scope of algorithmic suggestions. These acts of resistance, which may consist of bypassing the algorithm or looking for a music in a more traditional way (than MRS), reflect the need for users to retain some degree of independence. Furthermore, it highlights the need for algorithmic systems to adapt to user preferences, rather than treating them as fixed attributes, which risks limiting the diversity of music discovery.

In conclusion, the interaction between users and MRS makes a tension emerge: algorithmic convenience, simplifying discovery and the listening activity per se, is faced by the need for personal control, in order to suit the users evolving taste and keep their music choice seemingly authentic. These insights are crucial because they reveal that for MRS to remain engaging, they must adapt to users' changing needs rather than relying on static preferences.

4.4 Taste and Musical Identity

An interesting pattern that emerged from the interviews was the extent to which users consider music as an essential part of their identity. For many of them, it resulted that music is a fundamental medium to communicate who they are and how they relate to the world around them. Interacting with MSP therefore becomes an activity through which users project their values, personality and emotions, ascribing to music the role of an active tool in their self-definition process.

4.4.1. Music as a Reflection of Personal Identity

A significant proportion of participants (70%, or 10 out of 14) expressed that their music choices serve as an extension of their personal identity. For many, their playlists are a window into their inner world. As Rolf (Participant 13) aptly put it, "My playlist is like a diary… It's how I talk about myself without saying a word." Around 80% of participants described their taste as varied and evolving, also underscoring the dynamic nature of musical identity. These narratives align with the code of "Evolution of taste over time" and "Taste as identity," indicating a deep emotional and cognitive engagement with music beyond passive consumption. However, the remaining 4 interviewees affirmed that not all of the genres or artists they listen to completely represent their identity or reflect their personality. Therefore, if one likes an artist who mainly composes sad music, that does not mean that he is truly sad in his real life, but just that he finds his musical work appealing and nice to listen to.

4.4.2. A Desire for Distinction and Authenticity

Beyond mere entertainment, many participants also highlighted their desire to differentiate themselves from others through music. 64% of respondents expressed that they actively seek out lesser-known or niche genres, preferring music that feels personal and unique rather than mainstream. The reported reasons were diverse: from identifying as more unconventional, to feeling a stronger bond with the artist, the sample in analysis generally ascribed a special value to niche music. Additionally, people with niche music tastes were also described as more careful to what they listen to, interpreting this personal characteristic as a desire for researching finer music. The search for authenticity in music was therefore very important for interviewees. Especially in the context of music streaming platforms, where everything becomes available for everyone, having a more eccentric taste was felt as a way to carve out an individualized musical space in a multitude of items.

4.4.3. Emotional dimension of taste

The interviews also revealed an emotional dimension to taste. Nostalgia and deep emotional connections were frequent motifs, with Carlo (Participant 3) stating, “Certain songs feel like they belong to my past, and that makes them part of who I am today.” This emotional engagement supports DeNora’s (1999) theory of music as a medium for constructing and maintaining identity through everyday practices. Moreover, musical identity was often multifaceted and situational, with users acknowledging different “musical selves” depending on context or mood.

The literature further complements these findings by emphasizing taste as a “fundamental part of the self,” with the cultivation of diverse musical preferences linked to identity development and self-esteem (Chayka, 2024; Clark & Lonsdale, 2023). The notion that taste evolves as users engage with platforms reinforces the view of music listening as an active, reflective practice rather than a passive act.

4.5 Platform Perceptions and Critiques

Participants’ insight revealed a complex mixture of appreciation, skepticism, and critical reflection on how music streaming platforms, alongside MRS, operate and influence their listening experiences. This theme captures users’ nuanced attitudes towards platform features, commercial motivations, and the transparency of recommendation processes.

Approximately 75% of participants expressed a pragmatic appreciation of platforms like Spotify and SoundCloud for their convenience, breadth of content, and social features. For example, Alessia (Participant 1) affirmed that “Spotify is easy to use, and I like how it brings everything together in one place”, a statement that expresses how most of the interviewees felt. On the other hand, Soundcloud was more appreciated regarding the topic of artist support, saying, as it “feels more independent and helps artists get noticed, which I really respect” (Nadia, Participant 10).

Moreover, while being described as extremely handy and useful, users admit using MSPs mostly for convenience. Even if they are not completely satisfied with the algorithm or the interface per se, they pragmatically accept that the comfort offered by MSP often outweighs concerns about their functional and ethical limitations. Interestingly, while some users expressed loyalty to their preferred platforms, they simultaneously adopted a skeptical stance towards the power these companies wield over cultural consumption. Therefore, while partially being dissatisfied, users cannot ignore the value of such an incredibly musically extensive and practical tool, and keep using it. Criticizing some of its features does not entail hate or dislike, simply a partial dissatisfaction with the functioning of particular properties of MSP and MRS.

Alongside this functional appreciation, many participants voiced critical concerns about the commercial imperatives shaping platform behavior and the implications for user experience. About 80% of interviewees criticized Spotify's overt commerciality, perceiving it as privileging popular, mainstream artists over more diverse or niche content. The smaller artists are not as visible, obscured by market logics, and most of the users in this study's sample were really unhappy about this. This also aligns with Ruth et al.'s (2016) observations regarding editorial playlists tending to promote commercially viable music, potentially limiting diversity and fostering "filter niches."

Participants also discussed the opacity of recommendation algorithms as a significant source of frustration and distrust. Around 65% of users expressed skepticism about how the algorithms function and whether their suggestions were genuinely tailored or, on the contrary, biased by commercial interests. This echoes broader critiques in the literature on algorithmic opacity and lack of transparency (Lee, 2018; Karayakali et al., 2017), which can undermine user trust and lead to feelings of alienation. This is also connected to one of the most mentioned critiques to algorithmically generated recommendations, as to say repetitiveness. Since platform intercept users preferences, they are unable to account for situational and immediate changes (of any type, taste, situation, mood, etc.) and can often end up in defying the listener. This also leads to a decreased trust towards MSP and MRS, as users feel like their personal and individual complexity is sacrificed to try and satisfy as many users as possible.

In addition, **75**% of participants expressed frustration over the lack of transparency regarding how recommendations are generated. Pietro (Participant 12) even described the algorithm like a "black box", with "no idea why he was being shown a particular track". This uncertainty around the reasoning behind recommendations can easily fuel distrust, with users unsure of how their musical profiles are being shaped, interpreted or even manipulated.

In the end, users' experiences with music streaming platforms reflect an ongoing push and pull of control, one where they're constantly tweaking and adjusting their relationship with both the platform itself and the algorithms behind it. While these systems do a great job of offering convenience and a massive array of music to discover, they often miss the mark when it comes to keeping things fresh and personalized. Users want more than just what's already familiar; they crave variety, surprise, and recommendations that genuinely reflect their evolving tastes.

The real sticking-out points, though, seem to be trust and transparency. With the lack of clarity around how recommendations are made, it's no surprise that many users feel a bit disconnected from the process. If streaming platforms want to remain relevant, they'll need to shift their approach, moving beyond just serving up what's easy and popular, and focusing more on offering deeper personalization and genuine discovery.

As the landscape of music streaming continues to expand, understanding these subtle but crucial user frustrations and desires will be key. Platforms that can strike the right balance between smart, adaptable algorithms and genuine user trust will likely be the ones that thrive long-term, creating more than just a service, but a space where users feel truly heard and engaged.

5. Conclusion

5.1. Summary of Findings

This thesis ventures into and often underexplored terrain of music listening in the age of algorithms. Specifically, it aims at understanding how users interpret, negotiate and make meaning in the ongoing negotiation with music streaming platforms.
While most scholars have examined the topics of algorithmic logic, personalization systems and the consumption side of music streaming services, a persistent gap remains. We know that algorithms shape how we consume music, but the way this influence is experienced by users needs to be further investigated. This study therefore contributes to filling this gap, serving the need to answer the following question
How do music streaming users make sense of and engage with recommendation systems in their listening habits?

Much of the existing literature treats listeners either as passive recipients of recommendations and algorithmic dynamics or as skeptic users that do not fully grasp the power of MRS. This thesis flips that script. Drawing on fourteen in-depth interviews, this study aimed at highlighting the reflexivity, ambivalence and even creativity with which users engage with music recommendation systems. Furthermore, it does not assume *a priori* that being an active or passive user or resisting to algorithmic suggestions versus complying with them are binary and clear-cut oppositions. The goal is to uncover that user agency and algorithmic mediation are layered phenomena, which require a step-by-step analysis to understand how different ways of using MRS and MSP do not mutually exclude, but instead coexist and influence one another.

Key themes that emerge from the data include the psychological and emotional dimensions of music streaming: how users use platforms for mood regulation; how they perceive the algorithm as both a companion, helping them discover new music like a “close friend” (Alessia, Participant 1) and a mirror; and how they construct their musical identity through their interactions with these systems. Further central to this analysis are the tensions and conflicts between the predictability of the recommendations and the need for music discovery reported by the interviewed sample of users. Another crucial theme that emerged regards a general distrust of algorithms on the part of the user, which could be improved by providing more clarity especially in the recommendation process.

5.2 Limitations of this Research and Future Work

While the findings offer valuable insights into the complex relationship between users and recommendation systems, this study, as previously introduced in the method, has several limitations. First, the sample size of fourteen participants certainly does not represent the diversity of music listeners across the globe, nor does it account for potential variations in behaviour across different streaming platforms. Even if questions about what platforms users make most use of were included in the interview guide, further research could conduct a study cross-examining user behaviour across them. This would account for potential mechanism differences in the platforms which therefore lead to differentiated user practices.

Additionally, the participants' self-reported data may be subject to biases, as the research was based entirely on subjective observations rather than empirical and objective data. The sampling method also offers grounds for potential biases, as I only interviewed users from my personal network and the ones my interviewees, employing snowball sampling. Furthermore, another crucial aspect of the sample selection was the requirement of being music lovers, experts or connoisseurs, as I anticipated that they could offer richer insights into this theme due to their emotional, and at times professional, attachment to it. The goal of the research was ultimately not generalizing across all users, but to shed light on both the opportunities and limitations encountered by users in their everyday use of the platforms.

Future research could either focus on even narrower "niches" of users with clear and specific attributes (like music students, casual users, etc.) or broaden the scope to include a more diverse range of listeners with varying levels of expertise and cross-examine them. In addition, it could be interesting to explore how users actively or passively resist algorithmic curation by leveraging specific cultural practices or tool. For instance, some listeners may intentionally avoid or alter the recommendations by following niche creators or creating highly specialized playlists. Moreover, delving into the intersection between the influence on listening habits exercised by streaming platforms versus non-algorithmic contaminations, like participating in the local music scenes, attending live shows or relying mainly in physical media could represent an interesting ground for comparison.

5.3. Implications for Academic Fields and Digital Culture

These findings challenge the conventional view of user behavior by positioning individual opinion as not just subjective or arbitrary, but as a vital lens through which we can understand and compare different user behaviors. For cultural sociologists, this research shifts the focus from technology as an external force to technology as something co-created by users, with each user shaping their own musical identity in response to algorithmic curation. This reconceptualization of user engagement opens up new ways of thinking about culture and technology as inseparably interconnected. For media scholars, the study pushes beyond passive models of consumption, arguing that users' active interpretations and responses to algorithms are not random but are deeply patterned and influenced by personal context, social networks, and emotional needs. By taking these factors into account, we can develop more sophisticated frameworks for analyzing media consumption in algorithmic environments. For UX designers, these findings reveal the need for recommendation systems that acknowledge the full complexity of user agency. This can be done by incorporating more nuanced, adaptable features that respond to users' individual goals, moods, and evolving tastes. Instead of optimizing only for engagement and accuracy, platforms should strive for transparency and offer users real control over their experience. By embracing these insights, both researchers and designers can better understand the dynamics of user-algorithm interaction, not as a one-way flow of influence, but as a complex, reciprocal process where agency is negotiated and redefined in real-time, as enhanced by Actor-Network Theory.

6. Discussion

This study invites readers to rethink the relationshio between users and music streaming platforms, in a way that goes way beyond the typical binaries of control and submission. What ultimately emerged is that music streaming becomes an act of negotiation, where users constantly reconfigure their interactions with the system to make it work for their desires and necessities. It's a "dance of the human intention" against technological automation, but also one of ongoing adaptation to the unpredictable emotional terrains of daily life. With regards to this, the adaptability of algorithmic systems and streaming platforms to the complexity of the spectrum of human emotions and thoughts still needs to be intensely advanced and improved.

One crucial finding is that algorithms, contrary to a consistent body of academic work, were found to increase diversity, or at least stimulate users to explore music. Consequently, the way they engage with recommendations builds up into larger narratives of self, where they mold their sense of musical taste and identity. In fact, the process of sorting through suggestions, rejecting some, embracing others, becomes part of their journey of self-definition. The platforms and algorithmic systems therefore become a tool in the service of personal and social creativity and self-definition.

However, this creative potential is also counterbalanced by a tension in the very structure of the algorithms themselves. While they are built to facilitate exploration of content and also discovery of new items, they often get repetitive and are not able to capture all the aspects of something as complex as music taste. This speaks to a much larger question about personalization: when does personalization stop being personal and become prescriptive? The more sophisticated the algorithm, the more it risks becoming an echo chamber, reinforcing not only musical preferences but a set of behaviors that users may not even be aware they've been conditioned into. And herein lies an opportunity for design innovation, one that goes beyond just making recommendations smarter, but also making them more transparent, giving users the ability to actively mold their experience rather than passively accept it.

If we think of algorithms as partners rather than mere tools, we start to see the true potential of a more symbiotic relationship, one where the algorithm can learn to understand the user not only in terms of data points but in terms of complex, fluid human experience.Therefore, the algorithms inevitable predictability, at some point, can undermine the amazing and endless potential that music streaming platforms have. In fact, beside being very convenient tools to listen to music, they can also have an even educational/cultural spreading function, sharing content of every kind, culture and genre.

Ultimately, this study invites us to view algorithms not just as “decision engines,” but as active participants in the cultural and emotional landscapes of users. They are not neutral, nor are they fully in control, rather, they are part of a larger cultural ecosystem, where human agency and technological mediation are constantly shaping and reshaping each other.

References

Abdollahpouri, H., Burke, R., & Mansoury, M. (2020). Unfair Exposure of Artists in Music Recommendation. ArXiv.org. https://doi.org/10.48550/arXiv.2003.11634

Adiyansjah, Gunawan, A. A. S., & Suhartono, D. (2019). Music Recommender System Based on Genre using Convolutional Recurrent Neural Networks. *Procedia Computer Science*, *157*, 99–109. https://doi.org/10.1016/j.procs.2019.08.146

Anderson, A., Maystre, L., Anderson, I., Mehrotra, R., & Lalmas, M. (2020). Algorithmic Effects on the Diversity of Consumption on Spotify. *Proceedings of the Web Conference 2020*, 2155–2165. https://doi.org/10.1145/3366423.3380281

Ashwood, L., & Bell, M. M. (2016). Affect and Taste: Bourdieu, Traditional Music, and the Performance of Possibilities. *Sociologia Ruralis*, *57*(1), 622–640. https://doi.org/10.1111/soru.12135

Barata, M. L., & Coelho, P. S. (2021). Music streaming services: understanding the drivers of customer purchase and intention to recommend. *Heliyon*, *7*(8). https://doi.org/10.1016/j.heliyon.2021.e07783

Beauscart J.S., Coavoux, S., Maillard, S., & Carey-Libbrecht, L. (2019). Music recommendation algorithms and listener autonomy. Gouv.fr. https://documentation.insp.gouv.fr/insp/doc/CAIRN/_b64_b2FpLWNhaXJuLmluZm8tRV9SRVNfMjEzXzAwMTc%3D/music-recommendation-algorithms-and-listener-autonomy?_lg=fr-FR

Bello, P., & Garcia, D. (2021). Cultural Divergence in Popular music: the Increasing Diversity of Music Consumption on Spotify across Countries. *Humanities and Social Sciences Communications*, *8*(1), 1–8. https://doi.org/10.1057/s41599-021-00855-1

Bencherki, N. (2017). Actor–Network Theory. *The International Encyclopedia of Organizational Communication*, 1–13. https://doi.org/10.1002/9781118955567.wbieoc002

Blewett, C., & Hugo, W. (2016). Actant affordances: a brief history of affordance theory and a Latourian extension for education technology research. *Critical Studies in Teaching and Learning (CriSTaL)*, *4*(1). https://doi.org/10.14426/cristal.v4i1.50

Braun, V., & Clarke, V. (2006). Using Thematic Analysis in Psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Brinkmann, S. (2013). *Qualitative Interviewing*. Oxford University Press.

Celma, Ò., & Cano, P. (2008). From hits to niches? *Proceedings of the 2nd KDD Workshop on Large-Scale Recommender Systems and the Netflix Prize Competition - NETFLIX '08*. https://doi.org/10.1145/1722149.1722154

Celma, Ò., & Herrera, P. (2008). A new approach to evaluating novel recommendations. *Proceedings of the 2008 ACM Conference on Recommender Systems - RecSys '08*. https://doi.org/10.1145/1454008.1454038

Colley, A. (2008). Young People's Musical Taste: Relationship With Gender and Gender-Related Traits. *Journal of Applied Social Psychology*, *38*(8), 2039–2055. https://doi.org/10.1111/j.1559-1816.2008.00379.x

Denora, T. (2000). *Music in Everyday Life*. Cambridge University Press.

Eriksson, M., Fleischer, R., Johansson, A., Snickars, P., & Vonderau, P. (2019). *Spotify Teardown*. The MIT Press. https://doi.org/10.7551/mitpress/10932.001.0001

Eriksson, M., & Johansson. (2017). Repositorium für die Geschlechterforschung Tracking Gendered Streams. *Culture Unbound : Journal of Current Cultural Research*, *9*, 163–183. http://dx.doi.org/10.25595/1449

Ferwerda, B. B., Graus, M. M., Vall, A., Tkalcic, M., & Schedl, M. (2016). The Influence of Users ' Personality Traits on Satisfaction and Attractiveness of Diversified Recommendation Lists. *Conference on Recommender Systems*, *1680*, 43–47.

Finn, C., Abbeel, P., & Levine, S. (2017). Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks. https://doi.org/10.48550/arXiv.1703.03400

Foucault, M. (1992). *The history of sexuality*. Penguin Books.

Foucault, M. (2010). *Ethics: Subjectivity and Truth*. The New Press New York.

Foucault, M. (2022). *Confessions of the Flesh : The History of Sexuality, Volume 4.* Knopf Doubleday Publishing Group.

Friese, S. (2012). Qualitative Data Analysis with ATLAS.ti. SAGE Publications Ltd. https://doi.org/10.4135/9781529799590

Garcia-Gathright, J., St. Thomas, B., Hosey, C., Nazari, Z., & Diaz, F. (2018). Understanding and Evaluating User Satisfaction with Music Discovery. *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval - SIGIR '18*. https://doi.org/10.1145/3209978.3210049

Gillespie, T. (2014). The Relevance of Algorithms. *Media Technologies*, 167–194. https://doi.org/10.7551/mitpress/9780262525374.003.0009

Hesmondhalgh, D., Campos Valverde, R., Kaye, V., & Li, Z. (2023). The Impact of Algorithmically Driven Recommendation Systems on Music Consumption and Production. https://doi.org/10.13140/RG.2.2.22919.47525

Hesmondhalgh, D., Valverde, R. C., Kaye, D. B. V., & Li, Z. (2023, February 9). *The impact of algorithmically driven recommendation systems on music consumption and production - a literature review*. GOV.UK. https://www.gov.uk/government/publications/research-into-the-impact-of-streaming-services-algorithms-on-music-consumption/the-impact-of-algorithmically-driven-recommendation-systems-on-music-consumption-and-production-a-literature-review

Hesmondhalgh, D., Valverde, R. C., Kaye, & Li, Z. (2024). Critically Analyzing Platform Interfaces: How Music-Streaming Platforms Frame Musical Experience. *International Journal of Communication*, *18*(0), 22. https://ijoc.org/index.php/ijoc/article/view/21989

Hodgson, T. (2021). Spotify and the democratisation of music. *Popular Music*, *40*(1), 1–17. https://doi.org/10.1017/s0261143021000064

Iaquinta, L., de Gemmis, M., Lops, P., Semeraro, G., Filannino, M., & Molino, P. (2008). Introducing Serendipity in a Content-Based Recommender System. *2008 Eighth International Conference on Hybrid Intelligent Systems*. https://doi.org/10.1109/his.2008.25

Karakayali, N., Kostem, B., & Galip, I. (2017). Recommendation Systems as Technologies of the Self: Algorithmic Control and the Formation of Music Taste. *Theory, Culture & Society*, *35*(2), 3–24. https://doi.org/10.1177/0263276417722391

Kim, Y., Schmidt, E., Migneco, R., Morton, B., Richardson, P., Scott, J., Speck, J., & Turnbull, D. (n.d.). *MUSIC EMOTION RECOGNITION: A STATE OF THE ART REVIEW*. Retrieved March 22, 2023, https://ismir2010.ismir.net/proceedings/ismir2010-45.pdf

Komiak, S. Y. X., & Benbasat, I. (2006). The Effects of Personalization and Familiarity on Trust and Adoption of Recommendation Agents. *MIS Quarterly*, *30*(4), 941–960. https://doi.org/10.2307/25148760

Kotkov, D., Wang, S., & Veijalainen, J. (2016). A survey of serendipity in recommender systems. *Knowledge-Based Systems*, *111*, 180–192. https://doi.org/10.1016/j.knosys.2016.08.014

Lonsdale, A. J., & North, A. C. (2011). Why do we listen to music? A uses and gratifications analysis. *British Journal of Psychology*, *102*(1), 108–134. https://doi.org/10.1348/000712610x506831

Manen, M. V. (1990). Researching Lived Experience: Human Science for an Action Sensitive Pedagogy. In *PhilPapers*. Suny Press. https://philpapers.org/rec/VANRLE-2

Mansoury, M., Abdollahpouri, H., Pechenizkiy, M., Mobasher, B., & Burke, R. (2020). Feedback Loop and Bias Amplification in Recommender Systems. *ArXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2007.13019

Matrosova, K., Moussallam, M., Louail, T., & Olivier Bodini. (2024). Depict or Discern? Fingerprinting Musical Taste from Explicit Preferences. *Transactions of the International Society for Music Information Retrieval*, *7*(1), 15–29. https://doi.org/10.5334/tismir.158

Maxwell, J. A. (2012). *Qualitative Research Design : An Interactive Approach*. SAGE Publications

Miyazaki, S. (2012). Algorhythmics: Understanding Micro-Temporality in Computational Cultures. *Computational Culture*, *2*. http://computationalculture.net/algorhythmics-understanding-micro-temporality-in-computational-cultures/

Montecchio, N., Roy, P., & Pachet, F. (2020). The skipping behavior of users of music streaming services and its relation to musical structure. *PLOS ONE*, *15*(9), e0239418. https://doi.org/10.1371/journal.pone.0239418

Nicolaus, T. (2019). *The Platformization of the Music Industry - A Case Study of Bandcamp*. https://studenttheses.uu.nl/handle/20.500.12932/33928

North, A. C. (2010). Individual Differences in Musical Taste. *The American Journal of Psychology*, *123*(2), 199. https://doi.org/10.5406/amerjpsyc.123.2.0199

Noy, C. (2008). Sampling Knowledge: The Hermeneutics of Snowball Sampling in Qualitative Research. *International Journal of Social Research Methodology*, *11*(4), 327–344. https://doi.org/10.1080/13645570701401305

Pariser, E. (2011). *The Filter Bubble: What the internet is hiding from you*. Penguin Press.

Patton, M. Q. (2015). *Qualitative research & evaluation methods: Integrating theory and practice* (4th ed.). Sage Publications.

Pelly, L. (2018). *Discover Weakly.* The Baffler. https://thebaffler.com/latest/discover-weakly-pelly

Prey, R. (2018). Nothing personal: Algorithmic Individuation on Music Streaming Platforms. *Media, Culture & Society*, *40*(7), 1086–1100. https://doi.org/10.1177/0163443717745147

Prior, N. (2013). Bourdieu and the Sociology of Music Consumption: A Critical Assessment of Recent Developments. *Sociology Compass*, *7*(3), 181–193. https://doi.org/10.1111/soc4.12020

Raff, A., Mladenow, A., & Strauss, C. (2020). Music Discovery as Differentiation Strategy for Streaming Providers. *Proceedings of the 22nd International Conference on Information Integration and Web-Based Applications & Services*. https://doi.org/10.1145/3428757.3429151

Rentfrow, P. J., Goldberg, L. R., & Levitin, D. J. (2011). The Structure of Musical preferences: a five-factor model. *Journal of Personality and Social Psychology*, *100*(6), 1139–1157. https://doi.org/10.1037/a0022406

Reynolds, S. (2011). *Retromania: Pop culture's addiction to its own past*. Faber.

Roberge, J., & Seyfert, R. (2016). *What are algorithmic cultures?* ResearchGate; unknown. https://www.researchgate.net/publication/320979449_What_are_algorithmic_cultures

Ross, G. (2024). *More music released in a single day in 2024 than the entirety of 1989, study shows*. Mixmag. https://mixmag.net/read/more-music-released-single-day-2024-than-entirety-1989-study-streaming-news

Ruth, N., Spangardt, B., & Schramm, H. (2016). Alternative music playlists on the radio: Flow experience and appraisal during the reception of music radio programs. *Musicae Scientiae*, *21*(1), 75–97. https://doi.org/10.1177/1029864916642623

Saldana, J. (2015). *The Coding Manual for Qualitative Researchers*. SAGE.

Sandywell, B., & Beer, D. (2005). Stylistic Morphing: Notes on the Digitisation of Contemporary Music Culture. *Convergence: The International Journal of Research into New Media Technologies*, *11*(4), 106–121. https://doi.org/10.1177//1354856505061057

Schedl, M., Zamani, H., Chen, C.-W., Deldjoo, Y., & Elahi, M. (2018). Current challenges and visions in music recommender systems research. *International Journal of Multimedia Information Retrieval*, *7*(2), 95–116. https://doi.org/10.1007/s13735-018-0154-2

Shakespeare, D., & Roth, C. (2021). *Tracing Affordance and Item Adoption on Music Streaming Platforms*. https://doi.org/10.48550/arxiv.2109.03538

Siu-Lan Tan, & Al, E. (2013). *The psychology of music in multimedia*. Oxford University Press.

Smith, J. J., Jayne, L., & Burke, R. (2022). Recommender Systems and Algorithmic Hate. *Sixteenth ACM Conference on Recommender Systems*. https://doi.org/10.1145/3523227.3551480

Song, Yading, Dixon, D., & Pearce, M. (2012) *A Survey of Music Recommendation Systems and Future Perspectives*. The 9th International Symposium on Computer Music Modeling and Retrieval (CMMR).

Tang, M., & Pei-Syuan Jhang. (2019). Music discovery and revisiting behaviors of individuals with different preference characteristics: An experience sampling approach. *Journal of the Association for Information Science and Technology*, *71*(5), 540–552. https://doi.org/10.1002/asi.24259

van den Oord, A., Dieleman, S., & Schrauwen, B. (2013). *Deep content-based music recommendation*. NIPS'13: Proceedings of the 27th International Conference on Neural Information Processing Systems.

Vargas, S., & Castells, P. (2011). Rank and relevance in novelty and diversity metrics for recommender systems. *Proceedings of the Fifth ACM Conference on Recommender Systems - RecSys '11*. https://doi.org/10.1145/2043932.2043955

Villermet, Q., Poiroux, J., Moussallam, M., Louail, T., & Roth, C. (2021). Follow the guides: disentangling human and algorithmic curation in online music consumption. *Fifteenth ACM Conference on Recommender Systems*. https://doi.org/10.1145/3460231.3474269

Wang, X. (2024). Exploring the development of niche music in the digital age. *SHS Web of Conferences*, *181*, 04008–04008. https://doi.org/10.1051/shsconf/202418104008

Appendix A – Interview Guide

Personal Context and Listening Habits

1. Can you tell me a bit about your relationship with music?
2. How often do you listen to music?
3. Which streaming platforms do you currently use, and why?
4. Do you use a free version or a premium subscription? Why?
5. When did you start using music streaming services?
6. Can you describe a typical listening session?
7. Where do you usually listen to music (e.g., at home, during commutes, at the gym)?
8. Do you usually listen with headphones, speakers, or other devices?
9. Do you typically listen alone or often share the experience with others?
10. How do you decide what to listen to each day?
11. What role does music play in your life? Has this changed over time?
12. Have your listening habits changed since using streaming services?
13. How do you compare streaming with other ways of listening to music, such as CDs, vinyl, or digital downloads?
14. Do you feel more or less connected to music since using streaming platforms

Music Discovery and Interaction with Recommendations

15. How often do you pay attention to the platform's recommendations?
16. Which recommendation features do you use most? (e.g., Discover Weekly, Daily Mix, radio, suggested playlists, etc.)
17. Can you recall a time when a recommendation really surprised or impressed you?
18. How do you usually discover new music?
19. Do you actively seek music outside the platform's recommendations, or do you tend to stick to familiar songs and playlists?
20. Do you think streaming platforms have broadened your musical taste? How?
21. Are there any genres you feel are overrepresented or underrepresented in your recommendations?
22. Have you ever felt like the platform "knows you too well"?
23. Have you ever received completely irrelevant suggestions? Can you give an example?
24. What's the last track you listened to because of an algorithmic suggestion?

User Autonomy and Control

25. Do you feel in control of your musical choices when using the platform?
26. Do you think recommendations shape your tastes or reflect them?
27. Have you ever deliberately avoided algorithmic suggestions? Why?
28. What do you think of playlists curated by the platform compared to those by other users or yourself?
29. Have you ever used "private session" or other functions to influence what the algorithm tracks?
30. When did you last create a playlist? What motivated you?
31. Do you think algorithms influence how you listen (e.g., attentively vs. passively)?
32. Do you tend to follow recommendations or change your choices depending on mood or memory?
33. Have you ever felt "stuck" in a cycle of similar suggestions?
34. How do you think your musical tastes would evolve without algorithmic recommendations?

Identity, Taste, and Self-Reflection

(Goal: explore the role of streaming in identity and taste formation)

35. Do you think the music you listen to says something about who you are?
36. Has your view of your own musical taste changed since using streaming?
37. Are you proud of your musical taste? Why?
38. Have you ever felt judged by others for your recommendations or listening history?
39. Have you discovered music through suggestions that now feels central to your identity?
40. Do you ever try to intentionally diversify your musical taste?
41. Can you describe a moment when music made you feel more connected to yourself or others?
42. Do you re-listen to music from your past? How does that compare to new discoveries?
43. Would you say your tastes have expanded or narrowed over time?
44. What does having "good taste" or a "varied" taste in music mean to you?

Critiques and Perceptions of the Algorithm

45. Have you ever wondered how the platform decides what to recommend?
46. How transparent does the recommendation process seem to you?
47. Are you comfortable with your data being used to generate music suggestions?
48. Do you trust the algorithm to understand your taste?
49. Do you think streaming platforms influence mainstream musical trends?

50. Have you ever considered switching platforms due to dissatisfaction with recommendations?
51. How would you describe your relationship with the platform?
52. Have you read or heard criticisms of algorithmic recommendations? If so, did it influence your behavior?
53. If you could, what would you improve or change in the recommendation system?
54. Do you see music streaming more as a discovery tool, a convenience, or something else?

Final Questions

55. What does it mean to you to listen to music “attentively” versus as background?
56. Have you ever felt that the platform “forces” you into more passive listening than you’d have with physical media (vinyl, CDs)? How does this affect your connection to music?
57. Does the algorithm affect how you approach a song when you hear it for the first time?
58. Do you think the algorithm, in trying to give you what you like, ends up flattening musical diversity? How do you react when it feels like it’s standardizing your taste?
59. Do you feel freer in your listening thanks to access to infinite tracks, or do you think this leads to more “superficial” song selection?
60. Has the algorithm ever led you to rediscover a track tied to a strong memory? How does it feel when the platform resurfaces something that awakens a “past” part of you?
61. Have you ever made a conscious decision to disconnect from the algorithm’s influence, for instance by avoiding the platform or searching for music more traditionally?
62. Do you think the algorithm is changing the nature of the musical experience, making it more about quick, continuous consumption?
63. Have you ever discovered an artist you thought was unique, only to find out they were heavily recommended to others too?
64. How does it feel when your musical taste becomes “common” through the platform’s influence?
65. Have you ever forced yourself to explore genres outside what the platform recommends?
66. Is there music that feels defining for you, but that the platform never suggests? How do you deal with this disconnect between your identity and what the algorithm offers?
67. Does the algorithm seem “all-knowing” about your preferences, or does it often miss what you truly like?
68. Do you see the algorithm as an ally enriching your musical experience, or as a limit on your freedom of choice?

69. How important is novelty to your musical experience? If recommendations keep showing you songs you already know, how does that repetition affect you?
70. To what extent do you think the music the algorithm suggests affects how you see yourself as someone with particular musical tastes? Does this process change how you view yourself as a listener?
71. How surprising is the music the algorithm recommends to you? (Do you feel the algorithm reflects your musical identity well or surprises you with unexpected choices?)
72. How do you perceive the difference between spontaneous and algorithm-suggested musical choices? Does one feel more “authentic” than the other?
73. Do you ever stop to reflect on how much your musical choices are truly your own, or do you think your perception of taste is gradually shifting due to the platform “knowing you better”?
74. Is there anything I haven’t asked that you think is important to understand your experience with music streaming?
75. If streaming platforms disappeared tomorrow, how would your way of listening to music change?

Appendix B – Code List

Theme 1: Mood Regulation and Emotional Engagement

Code Group: Emotional Uses of Music

1. Mood regulation
2. Emotional engagement
3. Music as a coping mechanism
4. Contextual listening
5. Energetic/focus-based use

Code Group: Interaction with MRS

1. Customization of emotional experience
2. Frustration with mismatch between mood and suggestions
3. Manual adjustment of playlists for mood
4. Algorithm as emotional support tool

Theme 2: Algorithmic Influence on Discovery and Diversity

Code Group: Discovery Experience

1. Music discovery
2. Surprise and delight from recommendations
3. Repetitive suggestions
4. Lack of novelty

Code Group: Algorithmic Limitations

1. Over-specialization
2. Stagnation in discovery
3. Filter bubbles
4. Narrow content exposure
5. Repetition fatigue

Code Group: Appreciation of Algorithm

1. Algorithm expands musical horizons
2. Discovery of obscure artists
3. Initial support for exploration

Code Group: User Strategy

1. Switching platforms to find variety
2. Skipping or ignoring suggestions
3. Listening outside the app to diversify input

Theme 3: Perceived Agency and Control

Code Group: Active Listening Behaviors

1. Playlist creation
2. Manual curation

3. Intentional selection
4. Training the algorithm

Code Group: Passive Listening Behaviors

1. Letting the algorithm decide
2. Ambient or background use
3. Algorithm as convenience

Code Group: User-Algorithm Relationship

1. Resistance to algorithmic control
2. Negotiating with the algorithm
3. Shaping recommendations
4. Algorithm as a co-curator

Code Group: Control and Autonomy

1. Desire for personalization
2. Switching platforms for more control
3. Frustration at loss of agency
4. Conscious deviation from recommendations

Theme 4: Taste and Musical Identity

Code Group: Identity Expression

1. Self-expression through music
2. Music as a mirror of identity
3. Taste as identity marker
4. Non-normative preferences (e.g., happy person liking sad music)

Code Group: Authenticity

1. Preference for underground/independent music
2. Avoidance of mainstream suggestions
3. Search for unique or niche sound
4. Validation of individuality through music

Code Group: Curation as Identity Work

1. Pride in self-made playlists
2. Sharing taste as a social/identity statement
3. Curatorial role of listener

Theme 5: Platform Perceptions, Trust, and Algorithmic Opacity

Code Group: Platform Evaluation

1. Platform satisfaction
2. Preference for niche vs. mainstream platforms
3. Hybrid platform desire (Spotify + SoundCloud)
4. Commercialism critique

Code Group: Transparency and Trust

1. Opacity of recommendation system
2. Lack of clarity on how recommendations are generated
3. Trust vs. skepticism in MRS
4. Suspicion of data-driven personalization

Code Group: Bias and Limitations

1. Repetitiveness in suggestions
2. Mass-market bias
3. Disappointment in niche genre recommendations
4. Algorithm as not understanding individual taste

Code Group: Platform Switching Behavior

1. Use of alternative platforms
2. Seeking better personalization
3. Mistrust driving diversification of sources

Appendix C – Informed Consent Form

Project Title and version	Beyond the Algorithm: How Users Interpret and Navigate Music Recommendation Systems on Streaming Platforms
Name of Principal Investigator	Letizia Josephine Galati
Name of Organisation	Erasmus University Rotterdam – Erasmus School of History, Culture, and Communication.
Purpose of the Study	This research will inform my Master Thesis project. The purpose is to explore how algorithmic recommendation systems and music streaming platform influence our listening habits
Procedures	You will be asked questions about music streaming platforms, algorithms and listening habits
Potential and anti-cipated Risks and Discomforts	There are no obvious physical, legal or economic risks associated with participating in this study. You do not have to answer any questions you do not wish to answer. Your participation is voluntary and you are free to discontinue your participation at any time.
Potential Benefits	Participation in this study does not guarantee any beneficial results to you. As a result of participating you may better understand your motivations and values behind your practice.
Sharing the results	If desired, you may receive a digital copy the finished research.
Confidentiality	Your privacy will be protected to the maximum extent allowable by law. No personally identifiable information will be reported in any research product. Moreover, only trained research staff will have access to your responses. Within these restrictions, results of this study will be made available to you upon request. As indicated above, this research project involves making audio recordings of interviews with you. Transcribed segments from the audio recordings may be used in published forms (e.g., journal articles and book chapters). In the case of publication, pseudonyms will be used. The audio recordings, forms, and other documents created or collected as part of this study will be stored in a secure location in the researchers' offices or on the researchers password-protected computers and will be destroyed within ten years of the initiation of the study.

Right to Withdraw and Questions	Your participation in this research is completely voluntary. You may choose not to take part at all. If you decide to participate in this research, you may stop participating at any time. If you decide not to participate in this study or if you stop participating at any time, you will not be penalised or lose any benefits to which you otherwise qualify.
Statement of Consent	Your signature indicates that you are at least 18 years of age; you have read this consent form or have had it read to you; your questions have been answered to your satisfaction and you voluntarily agree that you will participate in this research study. You will receive a copy of this signed consent form.
Audio recording	I consent to have my interview audio recorded ☐ yes ☐ no
Secondary use	I consent to have the anonymised data be used for secondary analysis ☐ yes ☐ no
Signature and Date	Signature: The researcher: Date: