Experiences of Non-Mainstream and Minority Users with Music Recommendation Systems

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ABSTRACT

Music recommendation systems are widely used to consume music. However, non-mainstream users often receive recommendations that do not align with their individual preferences. While the algorithmic aspects of these systems have been extensively studied, this paper focuses on understanding the user perspective and experience. For this purpose, we carried out a focus group based study with Turkish-origin users and Dutch users in the Netherlands who use music recommendation systems such as Spotify. The results show that the experiences expressed by the participants were consistent with the literature on how recommender systems perform for minority users. Particularly, we observed that most of these issues are related to the more generic popularity bias, which further underlines the need to improve the representation of users with non-mainstream music preferences.

CCS CONCEPTS

• **Human-centered computing** → Interaction paradigms; *Empirical studies in HCI*.

KEYWORDS

Mainstream bias, Minority recommendations, Music recommendation

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1 INTRODUCTION

The rise of music streaming platforms like Spotify, Apple Music, and Last.fm has made music a very accessible source of entertainment for a large number of people. Music is often used to reflect local issues, and studies suggest that particularly adolescents use music preferences to express their identity [16, 24, 30]. Researchers have estimated that 90% of the population listens to an average of 32 hours of music per week, highlighting its widespread influence [28].

Music Recommender Systems (MRS) play a crucial role in guiding users by suggesting music, even when their preferences are unclear [26]. However, despite suggesting songs based on user tastes, MRS are prone to provide unsatisfactory recommendations influenced by various factors. Current MRS dynamics often lack detailed consideration of user-item interaction and content-based item descriptions, contributing to these shortcomings [33], with as a result that algorithms perform best for mainstream users and mainstream music.

Mainstream music is largely Western-dominated due to user demographics [6]. In contrast, ethnic or niche music represents minority user groups, reflecting their culture, traditions, and community [12]. Factors like language, region, and genre preferences contribute to the appeal of ethnic music to these specific user groups.

The predictive capabilities of the MRS face a significant challenge when users tend to find diverse music genres or ethnic music and these minority groups often receive poorer recommendations than those whose tastes align with popular music [22, 28]. Poor recommendations are reported to result from a combination of a minority user base and limited availability of minority music [12] due to missing data [25].

In this exploratory study, we focus on user-centric issues related to MRS for users with a Turkish background who live in the Netherlands. As in many European countries, the Turkish diaspora forms a large minority in the Netherlands, with relatively well-investigated connections with Turkish music [19]. In focus groups, we investigate the mix of English-language, Dutch and Turkish music and the different music genres that they listen to, and then investigate their experiences with MRS with respect to their individual tastes and (cultural) backgrounds.

2 LITERATURE REVIEW

The recommendation of music distinguishes itself from movies, books, and other products due to specific factors [33]. Songs vary in duration and are typically consumed in a sequential manner. Further, the user context is crucial, as users may engage with music actively or passively, depending on the occasion or mood. The purpose of listening also holds significance. In this literature review, we briefly discuss the current state of existing MRS, followed by a discussion on how to balance algorithmic performance and user experience. We then dive into the issue of popularity bias and how this affects non-mainstream, ethnic music and its listeners.

2.1 Existing MRS

Numerous studies have investigated various elements of the user and the user context to be taken into account for optimal music recommendations [31]. It has been observed that automatically recommending music goes – or should go – beyond suggesting music that is identical to a user's typical listening preferences; It

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entails proposing potentially intriguing pieces that may not have clear connections to the user's listening history [5].

Current music recommender systems prioritize accuracy and user preferences, but often neglect joint item selections and the recommendation moment. Bonnin and Jannach [4, 12] analyzed evaluation methods, revealing a common focus on specialist demonstrations [12, 35] and playlist prediction experiments [12, 29]. However, these approaches may overlook the impact of recommendations on the user experience, potentially leading to inaccuracies and misrepresentations [20]. What these algorithmic approaches have in common is that they all suffer, in one way or another, from data biases, as explained in the next subsection.

2.2 Balancing Algorithm and User Experience

Algorithmic advancements in recommender systems have been significant, yet the user experience has not received equal attention [33]. Listeners often distrust algorithms on music recommendation platforms when they lack understanding of how they operate [34]. Additionally, users tend to notice and remember unpleasant recommendations more than enjoyable ones, posing an additional challenge [1].

Platforms relying on user input for results emphasize the importance of a shared vocabulary between users and creators for descriptive labels related to genre, artists, and track titles. This alignment is often lacking, especially with ethnic music [18, 27].

A study on four standard recommendation algorithms found significantly poorer accuracy when dealing with non-mainstream users [22]. Despite being underrepresented, proper music recommendation is still crucial, requiring considerations beyond continually improving collaborative filtering methods [31].

Prior studies focused on fairness, but overlooked how minority users perceive belonging in recommender systems. Our user-centric study assesses satisfaction, examining content alignment and goal achievement, focusing on the Turkish minority in the Netherlands.

2.3 Popularity Bias

Research [7, 22, 37] suggests that people gravitate towards popular music, leading to limited data for less popular items. This scarcity hinders recommendations for items with few ratings, known as long-tail items [8, 22]. As a result, users favoring less popular items may not receive suitable recommendations [7].

The scarcity issue is particularly problematic for users who (occasionally) prefer niche music [17], as their preference for less popular items results in inadequate recommendations. This phenomenon is attributed to popularity bias, causing an over-representation of overall popular (mainstream) items in recommendation lists [21, 22]. Interestingly, studies have shown that perceived diversity in recommendations simultaneously positively influences list attractiveness and negatively impacts decision difficulty [13]. On the other hand, Willemsen's [39] work on movie recommendations shows that diversity contributes to list appeal, potentially reducing choice difficulty and enhancing satisfaction.

Popularity bias in recommender systems leads to the overrepresentation of popular items, leaving less popular ones underrepresented [23]. This bias tends to recommend mainstream music favored by the majority of users, reinforcing mainstream bias. Mainstream music, in this context, is typically Western music, especially English-language music [33].

2.4 Cultural Aspects

People worldwide share a love for music, but its perception and interpretation vary culturally [3]. Music genre preferences can be global or region-specific, influenced by factors like exposure at a young age. Adolescents often mirror their parents' music tastes, with correlations showing a connection between parental and children's preferences [36]. This influence is likely due to the shared living environment exposing children to their parents' favorite music [24].

Accessing ethnic music is challenging, as it does not fully align with Western-based concepts in current content-based methods. Missing details like performer and composer names contrast with available information that usually is not taken into account, such as local instrument names, ethnic background, recording details, and music function [9]. The relatively small user bases in ethnic music collections make it even more challenging to apply common algorithms such as collaborative filtering [10].

The music of the Turkish diaspora in Northern Europe, which is the focus of our study, spans various genres, including traditional Turkish music, classical Ottoman music, and contemporary genres influenced by Western music. Fusion genres, blending Turkish and Western elements, contribute to a diverse musical landscape within the diaspora. This includes collaborations in genres such as pop, hip-hop, electronic, and world music, reflecting the cultural interchange between the Turkish community and their host countries [19].

3 METHODOLOGY

We decided on a focus group methodology to gather comprehensive user perspectives. By inviting groups of Turkish and Dutch MRS users, we aimed to evoke in-depth discussions that delve into the users' various experiences, preferences, and expectations from MRS. The focus group questions were intentionally open-ended and neutral, to encourage participants to express themselves without undue influence on their thoughts.

The questions in the Turkish focus group were inspired by four different measurement models for user satisfaction. However, we have not used any specific dimensions or scales from these models to measure our qualitative results. These models provided us with ideas on how to formulate questions for our focus groups. The first one is the Technology Acceptance Model (TAM), previously applied in the context of movie recommender systems [2]. We also utilized the System Usability Scale (SUS) as a base for questions regarding user satisfaction with the platform. This model has been previously deployed, such as in the evaluation of a online music documentation system [40].

The exploration of music listening diversity has revealed associations with Hofstede's cultural dimensions [14, 15]. [32] concludes that cultural and socio-economic similarities better reflect similarity in music preferences than geographic distance. Therefore, we took aspects of Hofstede's dimensions into account as well for the design of the focus group sessions. Further, we aspired to understand if users experience a sense of belonging and recognition while using the platforms. The Achievers Workforce Institute [1]devised a blueprint to gauge the sense of belonging, outlining six major domains. We have adapted this blueprint for the context of a music recommender system to assess user satisfaction on the platform.

Following the Turkish focus group study, we conducted a similar focus group with Dutch participants, the majority in the Netherlands. The aim was to assess if they shared similar experiences, helping us understand if popularity bias affects both majority and minority groups alike. The focus group questions were based on findings from the Turkish study, allowing Dutch participants to reflect on them.

4 RESULTS

For the study, we conducted 3 focus groups with a total of 11 participants. Each session lasted one hour. The first two focus groups comprised 4 and 3 Turkish participants, respectively, while the third focus group involved 4 Dutch participants.The focus groups were conducted in English. Two out of the seven Turkish participants immigrated from Turkey, while the rest were born in the Netherlands. Anonymity was maintained during the transcription process by assigning names based on the order of participation (e.g., Participant 1 from focus group one was called P1.1).

Open coding was employed, extracting brief snippets from the transcripts, and categories were developed based on these snippets. The result section will encompass themes derived from these codes, along with the corresponding responses of the participants associated with these themes.

The results are divided into subsections based on axial coding. The first section focuses on participants' choices, the second on Dutch music culture, the third on their association with ethnic music, the fourth and fifth on their searching experience in the MRS and its recommendations. The final section discusses the participants' approaches to and use of the platform.

4.1 Personal choices

The focus groups aimed to explore the user experiences of non-mainstream users in MRS, with a specific focus on understanding the music preferences of the participants. Turkish focus groups showed diverse music preferences. By contrast, the majority of the Dutch participants described their music taste as aligning with mainstream music, with one associating it with context and mood while listening, along with the level of concentration.

While all participants used Spotify, not everyone relied solely on this platform for music. The participants' choice of additional platforms was influenced by the constraints they perceived with Spotify. P1.4 expressed, *"I don't use Spotify because I feel like it's a box,"*, as she felt that she cannot get out of the recommendation loop and P2.3 shared his thoughts on using SoundCloud: *"And for example, I listened a lot to SoundCloud, and SoundCloud is accessible, and that's why I like it a lot sometimes."*

[1]https://www.achievers.com/resources/white-papers/workforce-institute-belonging-blueprint/

4.2 Dutch and mainstream music landscape

The majority of Turkish participants identified as non-mainstream listeners. P1.2 explicitly disregards mainstream considerations, stating, *"I'm searching for the music that I like, so I don't care about the mainstream."*

Some participants did feel external influence based on their music taste. P2.1 mentioned a feeling of alienation and judgment regarding his interest in melancholic Turkish music, stating, *"But I also heard people say, like. And stay away from people that listen to that kind of music. So I think it's a I think I'm looking for the word stigma around."*

P1.3 and P1.4 mentioned not listening to famous artists like Taylor Swift or The Weeknd. However, they acknowledged encountering mainstream music in public spaces like stores or supermarkets, where popular songs are played for a broader audience as a result of a "Taylor Swift Effect".

The majority of Dutch participants said that their platform is English dominant. This is due to the ratio of English to Dutch songs present on the platform. Even if the participants had a history of searching Dutch music on the platform, the recommendations would not show Dutch music that often.

4.3 Cultural aspects

The Turkish participants showed a high inclination towards listening to Turkish music, influenced by their early childhood and the impact of their parents in shaping their preferences, which is a recurring theme in the data. For example, p1.4 said, *"My parents always listen to Turkish music, and I always listen to Turkish music."*

P2.2 said, *"If you look at songs, most of the time, the English songs or popular songs almost immediately appear on all of it. So you can see the lyrics some. But if you go to Turkish songs or a bit less popular songs, most of the time they don't have the lyrics."* This issue is not because the songs are Turkish, but rather due to the overwhelming effect of popularity bias.

By contrast, Dutch participants expressed that as there are not that many Dutch songs on the platform and because they are well categorized, it is easy to find them, but at the same time, P3.4 mentioned that you need to have the right vocabulary to find them on Spotify; otherwise, you have to resort to using YouTube.

4.4 Searching in MRS

This section delves into user experiences with music discovery, highlighting the impact of popularity and user feedback loops. The search function was found ineffective for discovering new artists, largely reflecting recent music preferences. P1.4 addressed Spotify's artist discovery challenge, stating: *"Yeah. And in case you have to search, still, uh, it's sorted the list based on the popularity. So it's really hard to find kind of unpopular, unknown or niche."*

The Turkish participants also found themselves in loops of the same songs, as they couldn't find diversity in their recommendations. P1.3 said: *"Like if you listen to a song once and then you have to listen to it for a while, they keep trying to do it again. Okay, no, I listen to it enough"*. One reason they found this to be the case was the representation of niche music. P1.2 expressed: *"The same kind of artists. And so it's not really like trying to push boundaries on that."*

The Dutch participants did not get many recommendations for songs that were not in either English or Dutch. P3.4 did receive recommendations for Spanish tango music because she listens to it a lot, while P3.2 receives German and French recommendations, also due to his listening behavior. So, the platform itself seems not to promote diverse music. P3.1 did feel that his playlists were diverse, but also said that he does not pay too much attention to it. P3.4 said that she has diverse playlists but not her daily playlist.

4.5 Recommendations of MRS

Some Turkish participants expressed feeling restricted by Spotify's recommendations, perceiving them as not aligned with their preferences and often recommending mainstream music. P2.1 emphasized this point by stating, *"But then I guess something like Rihanna or something. And I never, never listened to it. Yeah. I don't know why it recommends that with it's not like I share an account or something."*

The Turkish participants faced challenges in discovering new and niche music, often finding themselves stuck in the same loop of recommendations, as P1.2 stated: *"And then it's matched with my music taste. Okay, but I agree with her that it doesn't recommend something new."* Similarly, P2.2 expressed a similar sentiment about recommendations, saying, *"For example, if you are sad, I think Spotify does a good job in putting you in that sad mode."*

The Dutch participants acknowledged the role of majority bias, but were uncertain about its significance and effects. P3.2 believed that the algorithm provides him with different music items that he would not have been able to find on his own, along with an assumption that majority bias would be higher without Spotify, since having Spotify recommendations is still better than having random recommendations. P3.1 agreed that there is a majority bias but stated: *"I think Spotify is not a saint. It is not here to please the world. It's here to make money,"* and he is content with the platform, believing that there are better options for exploring new music, as according to him Spotify caters primarily to mainstream users.

Participants did notice changes in recommendations when changing the country. P1.2 mentioned, *"I'm also getting a recommendation for Dutch music here, but that's not the case in Turkey."* P2.1 experienced it while traveling to a different location, stating, *"I'm experiencing sometimes it's, uh, mostly the top lists that are changing for me that are recommended by, for example, if I go to Berlin, my Spotify list changed completely to just that type of music."*

While the change of location did affect the recommendations for the Turkish group, the Dutch participants did not experience it. However, they said that this could be due to several reasons, as one of them does not even pay attention to the homepage and goes directly to the already selected playlist, while the other does not use the platform while abroad.

4.6 Approaches and functionality of the platform

While the recommendation list often aligned with participant's preferences, they also encountered random recommendations, as mentioned by P1.1: *"Um, I think I was, uh, listening to this weekly discover, uh, feature in Spotify, and it was very well aligned with my current taste, etc. but now, uh, I don't know. Last two times. Okay. It is completely random."*

Additionally, they found it challenging to discover new songs through this functionality, as most of the songs in this functionality are those that are already very popular, with P1.4 expressing her experience: *"Discover Weekly. It's also quite a lot filled with old songs, I think. And yeah, it doesn't really help you with finding new stuff."* P1.2 resonated with this sentiment, saying, *"I think for the new artists, a bit harder to find them."*

However, the Turkish participants also felt that they were sometimes stuck in a loop of similar songs, and the recommendations may not always align with their preferences, as mentioned by P2.3 *"But if you like, as I use like just push on the magic shuffle and you think that everything will come, uh, very good and very precise, aligning with your music tastes, then that's a bit more difficult, I would say."* Despite the availability of different options, the results suggest that these methods may not effectively address the users' preferences or expectations.

5 DISCUSSION

As an overall summary of the results, we aimed to investigate the user experiences of ethnic and non-mainstream users in the platform, but the issues we encountered appear to be more related to the general issue of popularity bias within music recommendation systems rather than being specifically tied to specific countries, languages, or cultures.

The results reaffirm points from the literature review while highlighting new information. The participants in the focus groups shared a diverse taste in music, including both popular and less-listened-to genres. This aligns with the literature [16, 24, 30] confirming that people use music as a means of interpretation and expression of their identity.

The Turkish participants expressed interest in exploring new music rather than relying solely on their previous listening patterns. However, they found their current recommendations not diverse enough, making it challenging to discover new music [8, 22]. As self-identified non-mainstream users with a preference for niche music [17], the search functionality did not provide much assistance in finding new artists [18, 27]. Their current consumption patterns influencing recommendations create a "rich get richer" phenomenon, where repeated listening to the same songs impacts the accuracy of recommendations for their preferences [11, 22].

On the other hand, the Dutch participants rely heavily on recommendations from their friends and are not as inclined to discover new music. They also felt that the platform itself did not provoke them enough to explore music outside their domain. Since the Dutch participants involved in the focus group associate themselves with more mainstream music, they hadn't noticed the "rich get richer" phenomenon as much as the Turkish population. Also, since they use the platform more like a record player or a platform to keep libraries of the songs they listen to, their usage patterns differ significantly.

In the Turkish group particularly, participants observed a bias towards popular content in recommendations, as they were often suggested songs in English or by famous artists, which is in line with [33]. This bias created discomfort for them when exploring new music, given the overemphasis on popular choices [21, 22].

Additionally, the platform struggled to assist users in discovering traditional Turkish folk music [23].

The Dutch participants also observed bias, as one of the participants felt that popular songs were recommended. They found the platform to be English-dominant and did not get recommendations for songs that were not in either English or Dutch. The Dutch participants found that finding Dutch songs on the platform is easier due to categorization, but they also mentioned that these songs need to be present on the platform but do not appear in the recommendations even if they have been listening to them for a while.

The results imply that difficulties in finding minority music largely stem from popularity bias and feedback loops within the platform. Users must actively seek ethnic music, as it is not frequently recommended. However, users may be reluctant to invest extra time in alternative methods provided by Spotify to discover non-mainstream or ethnic music. Also, even though Dutch participants were mainstream listeners, they still experienced some degree of majority bias. Mainstream listeners were not exposed to, or attentive to, the issues faced by the Turkish group, highlighting how mainstream users tend to overlook minority issues due to lack of exposure. Raising awareness among the majority is crucial to making minority issues relevant, but the study's small sample size limits generalization.

6 CONCLUSION

Initially, we assumed that minority communities with specific music tastes might face specific challenges in an environment dominated by majority users with different preferences. To explore this, we focused on the Turkish community in the Netherlands. Our results indeed confirm that users with a preference for Turkish music do encounter difficulties while receiving poor recommendations and struggle to find niche and non-mainstream songs.

However, it appears that this challenge is not exclusive to the Turkish community or their music taste: it rather seems to be a symptom of a broader issue: popularity bias and the recurrent recommendation of popular songs, keeping users in a repetitive loop that hinders the exploration of new music.

A main insight from our study is that all forms of actual and perceived disadvantage or neglect of minority users were observed by these users to have popularity bias as the main underlying cause. This implies that the largest gain can be reached by reducing popularity bias in general and that popularity bias should be taken into account while seeking specific solutions for underrepresented user groups.

The practical benefits of reducing popularity bias, especially from a commercial perspective, might seem less reasonable where promoting a smaller selection of popular music might be more profitable than catering to the long tail. However, catering to minorities is beneficial in the long run, since users who favor non-mainstream music generally have more extensive user profiles and hey tend to listen to a wider range of distinct artists compared to those who prefer mainstream music [23]. Including them would also expand the horizons of the users and increase diversity in the platform. Furthermore, a recent study showed that actively integrating music from local communities among globally popular songs plays a crucial role in user satisfaction, while being commercially attractive as well [38].

To summarize, the advantage of using an inclusive platform is likely not only to improve the recommendations through diversity but also to affect the attitude of non-mainstream users towards the platform. This approach ensures a more diverse and inclusive user experience, fostering a sense of community and belonging among all users, regardless of their mainstream or minority status. It also helps in retaining a wider user base in the long run, contributing to the platform's sustainability and growth.

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