CAN WE LISTEN TO IT TOGETHER?: FACTORS INFLUENCING RECEPTION OF MUSIC RECOMMENDATIONS AND POST-RECOMMENDATION BEHAVIOR

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ABSTRACT

Few prior studies on music recommendations investigate the context in which users receive the recommendations, and what impact the recommendation has on the user. In this paper, we aim to better understand the factors that affect people's decisions as to whether they choose to listen to music recommendations and how the recommendations impact their music-listening behaviors. We conducted an online survey asking about people's past experiences on giving and receiving music recommendations. We found that in addition to the aesthetic qualities of music and the respondent's taste, expectations regarding the delivery (e.g., timing, persistence) of the recommendations, familiarity, trust in the recommender's abilities, and the rationale for suggestions were important factors. We discuss the implications for the design of music recommenders based on the findings, including better rationale for and accessibility of recommended music, improved saving options, and more targeted delivery at specific times. The data also suggests disparities in how people wish to receive music recommendations and what will influence them to listen to recommendations, versus how they would like to offer recommendations to others. In addition, the findings highlight the importance of music recommendations in people's existing social relationships and their role in building/improving new relationships.

1. INTRODUCTION

Music recommendation has been a well explored topic in the field of music information retrieval over the past few decades. Much of the recent research related to music recommendation focuses on improving recommendations for individual users or user groups by using various data or methods; for instance, user characteristics [22], tags or metadata [20, 21], or collaborative filtering [24]. In addition to more traditional content-based approaches, user behavior [6] and social/contextual features [20, 22] have also been explored to improve recommendation results.

However, few studies explore the broader process of users receiving music recommendations and what happens after the recommendations have been made. What kinds of contextual factors affect people to choose whether they listen or not listen to the music recommendations? Are there any changes that could be made in the way that people or music recommendation systems make the suggestions to improve the likelihood of someone listening to them? What kind of impact do music recommendations have on the user and the social relationships of recommenders and recommendees?

This paper aims to gain a deeper understanding of the user context where music recommendations happen, and the interaction between music recommendations and underlying social relations. We address the following research questions in this study:

RQ1: When people do not listen to recommendations, what are the reasons they do not do so?
RQ2: What can be done to improve the chances that people will listen to recommendations?
RQ3: What happens after the music recommendations? What are the perceived impacts of music recommendations on people's music listening behavior or social life?

We conclude the study by presenting a set of implications for designing music recommendation systems based on what we learned about people's post-recommendation behavior.

2. LITERATURE REVIEW

2.1 Music Recommendations

There is little literature about what happens after a user receives a recommendation, and how the chances of a user listening to the recommendation might be increased. Prior research seeks to understand the motivations behind sharing [12], but it has not necessarily examined *what comes next*, with regards to the recommendation's impact on a user's music listening behavior, social practices, and other aspects of their lives.

As commercial music streaming services become the primary way that many people access music, machine recommendation systems have become an important way to help music listeners find what they want to hear [19]. Jun et al. [11] proposed that there are two primary issues with providing "efficient music recommendation" (p. 1934). These issues are how accurately a recommender system can predict user preference and how accurately a system can assist with searching for new music [11]. The researchers identified that the flow, or sequence, of songs provided by recommender systems could be improved and suggested blending related recommendations into one seamless clip that takes a user's temporal-spatial information into account [12].

Studies like Lee et al.'s 2011 paper [12], one of the first studies on music sharing behavior via social networks, discusses the motivations behind why users share music. They examined social music practices on Korean social networks like Cyworld and Tisory, finding that "self-expression, ingratiation, altruism, and interactivity" are the main "social motivation factors" driving sharing behaviors on social media platforms (p. 716). Previously, most studies about online sharing music focused on piracy and the motivations behind those behaviors (p. 717). Understanding users' motivations for sharing music and the connections they make to their music may help in improving the likelihood that a recommendation is heard.

Su et al. [19] set out to examine the reliability of collaborative filtering recommender systems. They proposed a system called Recommendation by Tag-driven Item Similarity (RTIS), which takes both "play counts as implicit ratings and item tags as semantic preferences" into account (p. 304). Wang et al. [23] examined the effectiveness of a sequence-based recommender system that takes contextual information into account when providing recommendations, as "people usually have different [music] preferences and requirements under different contexts" (p. 231).

Zhang et al. [25] posit that music recommendation systems should, to the extent possible, simulate the kind of music recommendation that a friend might provide. Listeners are more likely to listen to recommendations from sources they trust, like friends. They built a recommendation framework called Auralist that used four identified factors relating to successful music recommendations: accuracy, diversity, novelty and serendipity. It was found that increasing serendipity in machine-based music recommendation improves user reception of recommendations.

In order for a music recommendation framework to be successful, Schedl [16] believes that recommendation systems must work at three levels: music content, music context, and user context (p. 1). Schedl's study focuses primarily on user-centric models in MIR and uses of geospatial location data for music recommendation. Based on their findings, they present an adaptable mobile player that automatically adjusts the playlist given user context.

2.2 Impact of Music Recommendations on Users

Music can have a memorable, sometimes lasting, impact on one's everyday life. Leong and Wright [14] examined social music practices in the home and the impact that various music technologies have on "people's sociality and in turn how various social practices affect people's interactions with technology" (p. 951). They found that participants that "explore and discover music together… provided opportunities for bonding, with new discoveries and insights into their shared interests in music" (p. 955).

Boer et al. [3] found that one's music preferences can help facilitate social bonding between strangers. Selfhout et al. [17] found that social music rituals and shared music preferences can contribute to adolescents' development of friendships. Boer and Abubakar [2] published a study to expand the evidence of the positive effects social music activities can have on "social cohesion and emotional well-being" (p. 1). They examined music listening behaviors in families and peer groups in four countries: Philippines, Kenya, New Zealand, and Germany. They found that "across four cultures music listening in families and peer groups contributes to family and peer cohesion, respectively" (p. 10).

North, Hargreaves, and Hargreaves' 2004 study [15] of everyday listening among 346 people provided "initial normative data on who people listen with, what they listen to (and what their emotional responses to this music are), when they listen, where they listen, and why they listen" (p. 41). Notably, this study indicated that users' music preferences are situationally dependent, and shifted based on where users are and who they are with. It also highlighted that music was most often accessed during activities independent of deliberate music listening, which we define in our study as passive listening.

Our study seeks to build upon the research of Lee and Price [13] on user personalities and personality characteristics and their relation to music information systems. Lee and Price identified seven personas that exemplified specific user music-listening attitudes, behaviors, and traits. User personas were indicative of how a user might access or curate music, as well as how that user might react to a music recommendation. In this study, we will specifically explore user behavior and how different personas may manifest in the context of music recommendation.

3. STUDY DESIGN AND METHOD

In order to understand user attitudes and behavior post-music recommendation, we designed a web-based survey. Links to the survey were shared via flyer in St. Petersburg, FL and Seattle, WA, posted online across various social media platforms, and disseminated in-person at local band events in St. Petersburg, FL. We received 219 total responses, with 92% of respondents from the United States, 2% from Canada, and 6% from other countries. 42% of respondents were male and 53% were female, with the remaining 6% identifying as other genders or preferring not to answer. The average respondent was 28 years old, with a youngest age of 15 and an oldest of 70 years old (Median: 27; Std dev: 9.71). We asked participants when and for how long they listened to music in their daily life. Respondents answered that they actively listen to music for 1-2 hours (Mean: 1.44 hours; Median: 1 hour; Std dev: 2.01) and passively listen to music for 3-4.5 (Mean: 4.43 hours; Median: 3 hours, Std dev: 3.69) a day. 95% of respondents typically listened to music through a streaming service like YouTube (72%), Spotify (64%), or Pandora (27%). Participants listened to music, actively or passively, during a wide range of activities. 89% of respondents listened to music while driving or commuting, 77% while working or studying, 74% while exercising, 73% while cleaning, and 63% while cooking.

We also asked respondents open-ended questions about what happens when they receive or give recommendations. Respondent answers were subject to multiple-coder grounded theory analysis [5]. Researchers looked for patterns in the answers given by respondents, and proposed qualitative codes to describe those patterns. The researchers generated a codebook for each question, though some questions were similar enough that certain codes could be used across multiple questions. The definition of each code and the rules for its usage were refined through an iterative process. Once codebooks were finalized, the codes were applied to responses using a consensus code model [9, 10]. Researchers coded answers independently, then met and discussed the applicability of codes until there was agreement between the three researchers for each code usage. The number of codes assigned to a response was not limited; some answers could be captured by a single code, while others were complex enough to require up to half a dozen codes. A copy of the codebook can be accessed at: https://tinyurl.com/ISMIR2019LeePritchardHubbles.

4. RESULTS AND DISCUSSION

4.1 Reasons for Not Listening to Recommendations

We asked respondents what influenced their decisions when they decided not to listen to a recommendation. Responses varied significantly depending on whether the recommendation came from an automated service or from another human being. Three general assessment categories were noted: recommendations tended to be rejected because the recommendation was aesthetically displeasing, because the recommender strategy was suboptimal, or because of external factors out of the control of the recommender.

For automated recommender services, respondents most often tended to judge whether or not to take recommendations based on aesthetic factors such as personal taste (71 respondents, 32.42%) or their level of familiarity with the artist, song, or genre (69, 31.51%). Respondents often rejected recommendations or suggested playlists that include artists/songs they know they hate. Other aesthetic factors included deciding against the recommendation based on descriptive information such as song title, lyrics, or style keywords (22, 10.05%). A few respondents also judged based on the artist's general popularity or based on visual cues like album art or band photography. Some commented on also relying on reviews or their perception of the artist (e.g., "*If I have heard bad reviews from peers or online, or think the band is against my values or promotes things I'm particularly against.*" (P20)). Several respondents stated that they will make a quick judgment as to whether they will continue to listen to the song or not after listening to a short snippet of a song, for about 10-20 seconds (20, 9.13%).

"*The beginning of the piece. If it doesn't sound catchy or doesn't have a decent layout of tone and rhythm, I'll skip it. I try to give all music a fair chance but sometimes I only have a certain window of listening time and I want to use it wisely*." (P192)

Factors external to the recommender system also played a substantial role in rejecting suggestions from automated services. Some respondents simply prefer a listening experience that does not involve recommendations (47, 21.46%). Other respondents mentioned not being in the right mood for the recommendation (34, 15.53%), alluding to the situationally-dependent music preferences of users [14]. A few also mentioned not having enough time to investigate recommendations or having inertia or a lack of interest.

"*This is my default state. I have to want to listen to a suggestion which really means that I'm in an exploratory mood*." (P163)

"*My mood mostly. I'm generally resistant to trying new things, but I always want to. Conditions must be perfect*." (P104)

Relatively few respondents criticized the recommendation strategy. Some chose not to listen based on whether the recommender service had given poor suggestions in the past (22, 10.05%), and a few mentioned annoying or inconvenient means of delivering suggestions, problems accessing the recommendations, getting too many recommendations, or simply needing an easy way to remember the suggestions.

"*The frequency of the suggestions making them easy to ignore and pin as spam*." (P42)

"*I'd love it if I could choose to add recommended music to a, 'listen later,' or, 'recommend to me again later,' list, just with the touch of a button*." (P196)

In some cases, the reasons people do not listen to music had nothing to do with the content of the music, but more with the context of the song or artist. Several users suggested that content-based music recommendations provided by recommender services will inherently be limited in their ability to predict the likelihood of someone listening to the music recommendation.

"*Honestly, a lot of reasons I won't listen to something is outside the sphere of music. How would a music streaming service know I don't want those recs because the fanbase is full of white supremacists or because the singer is a sexual predator?*" (P7)

For recommendations that came from other human beings, the recommendation strategy was the most important consideration in deciding whether or not to listen. The most common human factor was whether the recommender was reliable, or had given good or bad recommendations in the past (62, 28.31%); this consideration was much more prominent for human recommenders than for automated systems.

"*Whether or not I think they understand the very specific type of music I have asked them to suggest to me. Or if I have not solicited them if I will listen if I generally like the music they listen to and consider them to have 'good tastes'.*" (P49)

The underlying social relationship that a respondent had with a human recommender often played an important role in determining what the recomendee did with the music. In some cases, the feelings toward the recommender overrode other factors like the recommendee's taste in assessing the value of the recommendation.

"*It really depends on the person that gives me the recommendation. If it is someone I know I have a similar preference as, then I am definitely going to listen to it. Similarly, if it is someone I am friends with or just in general like, I will listen to it even if I don't know their music preferences that well. I won't listen to a song if I don't like the person or I know they like a kind of music I don't.*" (P38)

"*If I don't like the person I don't listen. If they're a jerk but I know they have good taste I check it out but I don't get back to them. I tend to associate my favorite songs with people I care about who introduced me to them originally.*" (P208)

Many respondents also mentioned that they easily forgot recommendations given by other people, and needed a means by which to remember them (34, 15.53%). A few mentioned annoying or inconvenient recommendation delivery tactics, or difficulty accessing the songs.

"*When people recommend music to me, it's also often not convenient. When I'm already using a streaming music, I'm already relying on them to suggest me new music. That's what they are for. However, when a friend recommends me music, it may come at a time when I'm not in the mood to explore but want to listen to some familiar favorites.* (P178)

Aesthetic considerations were also important in evaluating human recommendations. Familiarity (47, 21.46%) and taste (29, 13.24%) factors also played significant roles in deciding to skip recommendations from people, but were less prominent than with machine suggestions. External factors were also less prominent; quite a few respondents said they often did not have time to explore recommendations (24, 10.96%), and some also mentioned not being in the mood, having a lack of interest, or not wanting to take recommendations in general.

4.2 Things That Can Improve the Chance of People Listening to Recommendations

Additionally, we asked respondents what, if anything, could be done differently to make them more likely to listen to recommendations from streaming services or from other people, and responses were not dramatically different between the two. Two important considerations arose. One was the design or delivery strategy of the recommender or recommendation service. The recommender's design (broadly conceived for both services and people - when, where, and how the recommender or service chose to deliver suggestions) was important to respondents (services 36, 16.44%; people 43, 19.63%), as were components like whether information about the artist or song was provided with the recommendation, why the recommender made the suggestion, whether a clip was available for listening, and whether incentives for listening were provided. For recommender systems, the ability to manually change parameters was important, as respondents felt that they could receive more personalized recommendations.

"*I would be more interested if I would understand why those certain songs are being recommended to me (are the recommended songs based on similar tunes or because people who listen to my type of music like those recommended songs?). I would also probably listen to the recommended songs more if the recommendations were personal (such as seeing what types of people are listening to it, where it's being listened, what kinds of playlists it often appears in).*" (P13)

"*Maybe a better attempt at explaining why it was recommended (e.g., same scene, era, lyrical themes, mood, instrumentation, etc. of what I was already listening to).*" (P66)

For human recommenders, how often or how enthusiastically recommenders persisted in pushing recommendations, and whether the respondent's friends or acquaintances also liked the music being recommended, were also important factors that influenced people's decision to listen or not listen to music.

"*They could mention specific aspects of what I'd like. For example, 'I know you love Neko Case. This singer has a similar voice'.*" (P4)

"*A good description: the story behind the track creates an emotional connection to it and makes you listen more attentively. A direct link to the track (preview) available from everywhere. Even better if it can be previewed right in the messenger.*" (P120)

The social connection between the recommender and recommendee was mentioned repeatedly as a factor that might encourage to listen to the music: "*Make me like them? Or at least be charismatic enough and not a horrible garbage person.*" (P208); "*Make me better friends with those other people.*" (P26).

Second, respondents mentioned the importance of the content of the recommendations. Whether the recommendations were similar to personal taste - what the respondent likes or listens to - was most important (services 47, 21.46%; people 40, 18.26%). Respondents also mentioned basing recommendations on artist or genre/style similarity - i.e., musical similarity, rather than closeness to what the recommender likes. Other content factors included whether the person or system had a deep, intimate knowledge of the respondent; problems with older and newer listening desires conflicting (e.g., recommenders making recommendations based on old preferences); a desire for new songs unfamiliar to the recommendee; recommendations based on general popularity (or deliberately avoiding popular songs); and the ability to compartmentalize - to separate out genres or styles and get siloed recommendations for each. Additionally, some users desired contextual information about music and artists that may influence whether they would listen.

"*If they told me WHY they recommended a particular artist, or gave me some kind of cool "family tree" of the piece they're recommending (e.g., it featured a musician I liked).*" (P79)

"*If some of the algorithmic rationale was a bit more transparent in the messaging to the user (e.g. 'You might like this artist because they feature their bassist and you like other bass-forward bands' or 'Here is a collaboration between an artist you like and a different artist from a genre/label you like').*" (P161)

"*Essentially I'd like to feel like I'm geeking out about the music and somehow digging deeper into things (like the feeling of researching things on Wikipedia) rather than automatically thrown into a new radio station or a recommendation with no context.*" (P174)

Some respondents also talked about social features that aggregate people with similar music tastes or leverage the existing social connections among the listeners: "*Maybe tag artists that many of my friends listen to, sort of indirect friend suggestion.*" (P68); "*Aggregate 'listeners like you' - functionality where I can see what others with tastes similar to me like or are listening to.*" (P179).

We additionally asked what could be done to make it more likely that others would listen to music suggestions the respondent gave. A broad spectrum of responses materialized from this question. Common responses included providing a means for the person to listen (42; 19.18%), having similar music preferences (38; 17.35%), having a deep knowledge of the recommendee's personality or music preferences (34; 15.53%), pushing the recommendation hard or ginning up excitement about it (30; 13.70%), talking in person about the recommendation as opposed to via distance communication (29; 13.24%); and giving context or rationale for why the recommendation was made (24; 10.96%). In general, we noticed an asymmetric relationship between how participants felt about music recommendations from other people versus the music recommendations that they were giving to others. Most participants were able to articulate with specificity the different criteria they use to decide *not* to listen to music recommendations given to them, yet they generally exhibited high confidence that their recommendations to others were in fact listened to (further discussed in 4.3).

4.3 Post-Recommendation

We asked respondents about moments where giving or receiving recommendations led them to have more music-related interactions with another person. 102 (46.58%) said conversations followed about the song, artist, lyrics or genre, which often led to the discovery of mutual musical interests (50; 22.83%) and additional sharing of music (49, 22.37%). 41 (18.72%) described the opening up of a bond or deepening of a friendship with the recommendee, and an equal number talked about having shared experiences with the recipient, such as going to a concert, checking out a record store, or listening to music together at home or on trips. Several respondents talked about the depth and lasting impact of this kind of experience.

"*Once I shared a particular song with an acquaintance and we sat in rapt silence as we listened together, and the song ended up sparking one of the best conversations I had in my teens. Even now, whenever I hear even one song from that album, I remember what it was like when it was 'in the air' so to speak.*" (P27)

"*A friend I had spoken to about music prior had talked to me about an album and asked me to come over so that we could both listen to it on their record player. I was so moved listening to the entire album I started crying and talked to my friend about it, thus leading to a really deep meaningful conversation that deepened our relationship and understanding of each other. We eventually became best friends and this person is now really important to me*." (P82)

We also asked respondents whether they had shared a song, artist, or album with someone they knew in the past three months; whether they knew if the person to whom they had provided the recommendation actually listened to it; and how they knew the recommendation had been listened to. 148 (67.58%) of respondents responded both that they had made a recommendation and that the recommendee had listened to it. By far, the most common means of verifying this was through discussion. Of those who said the recommendee had listened, 103 (69.59%) said they had talked with the recommendee about the recommendation in person or via messaging or social media. 43 (29.05%) mentioned playing the song for the recipient or listening to the songs together, and a few mentioned making follow-up inquiries, singing the song for the recipient, or checking in on the recipient's listening or streaming activity within an application.

5. CONCLUSION AND FUTURE WORK

In this study, we investigated the contexts in which music recommendations occur, in order to improve understanding of the impact of music recommendations on people's lives and social relationships (and vice versa). The main design implications for recommendation systems based on our data analysis are as follows:

Needs for providing and receiving recommendations are asymmetric: In general, it seemed as if respondents were more comfortable broadcasting recommendations than receiving them. The systems and strategies that users would like designed for themselves to receive music differed from those they would build to recommend to others. They seemed more willing to be forward and persistent about pushing the recommendations out than they would prefer for recommendations aimed at them.

Music is an important tool for building social relationships: "Companionship (willingness to engage in social aspects of music listening)" [13] continued to be an important aspect related to music recommendations. Servicing people recommendations that come from their friends may help introduce a desired human element into the systems. Facilitating exchange of individual songs between people, and presenting these exchanges explicitly as recommendations, may improve the user experience beyond algorithmic or expert-curated recommendations. Automated suggestions drawn from friends' listening patterns or notifications of friends' activity ('Your friend just listened to: Track X') may not sufficiently substitute for intentional sharing of recommendations. This intention seems to be important, as the importance of a social relationship often overrode factors like musical tastes and preferences. People paid extra attention to music recommendations that came from people they cared about. Sometimes they were willing to listen to music that they personally had no interest in because they perceived it as an opportunity to spark an interesting conversation or have a shared experience and potentially improve their relationship with the recommender.

The co-listening experience was also important to many of our respondents. Co-listening was a factor that Spinelli et al. [18] identified as a significant social music behavior. Hagen & Lüders [7] noted that users on commercial streaming services might choose to follow each other to deepen interpersonal relationships, not necessarily because of "shared music preferences alone" (p. 10). Brown and Sellen [4] also discussed the social aspects of consuming music and how users can form or deepen relationships through listening to music together. Our findings enrich this literature by showing that our respondents viewed co-listening not simply as a way to ensure or verify that the recommendee listens to the recommendation, but also because that is how shared bonding experiences are created [14]; the recommendation could become the foundation or catalyst of the social relationship between recommender and recommendee. In music recommendation systems, perhaps a feature to support co-listening remotely (e.g., 'Your friend X is listening to Y. Would you also like to listen to it together?' and the system informing friend X that another user chose to co-listen to the song), rather than just providing the recommendation, might encourage people to be more willing to listen to the recommended song.

People desire for more personalized and contextualized recommendations: While the underlying social interaction is important, there is also a persistent desire for better algorithmic curation, over and above simple suggestions from friends. While recommendation systems have gotten more sophisticated and individualized over time, a variety of different recommendation requests surfaced - better matched to users' tastes, better matched to specific musical styles, better attuned to popularity and extramusical cultural associations, or compartmentalized based on different listening sessions. This kind of personalization could help meet the needs of the users in the long tail, who have stronger needs and wants regarding music recommendations (those labeled with the "music epicurean" persona by Lee & Price [13]). The context of the recommendation was also important to many respondents; they wanted to understand why the song was recommended to them, see the musical and social connections between the songs and artists, and know which friends were also listening to or interested in the music recommended to them. This desire for more contextual knowledge was a common theme for both machine and human based recommendations. While there is a fair amount of research available to support context-based music recommendation systems [1, 8, 11, 16], few have examined what might happen if users are provided insight into why an algorithm recommended something.

Some people are simply less interested in recommendations: In designing services, it may be valuable to note a significant recalcitrant population that is unreachable for recommendations, either because they do not want new music at all, or because they do not want new music from the service specifically (persona labeled as "Non-believer" in [13]). Part of this population still seems to respond to recommendations provided by people they know, especially if they feel like they can trust them. This trust was based on two factors: positive past recommendation experience, and how well the recommender understood the recommendee's musical taste. Designing a system to incorporate this social aspect of recommendation may help reach out to this reluctant population.

Many contextual factors need to be further investigated to gain a comprehensive understanding of the impact of music recommendations. In our future work, we plan to dive deeper into people's social music behaviors and explore perceptions of the value of specific social features such as collaborative playlists, co-listening, and music recommendations via videos and other audiovisual media.

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