ELUCIDATING USER BEHAVIOR IN MUSIC SERVICES THROUGH PERSONA AND GENDER

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ABSTRACT

Prior user studies in the music information retrieval field have identified different personas representing the needs, goals, and characteristics of specific user groups for a user-centered design of music services. However, these personas were derived from a qualitative study involving a small number of participants and their generalizability has not been tested. The objectives of this study are to explore the applicability of seven user personas, developed in prior research, with a larger group of users and to identify the correlation between personas and the use of different types of music services. In total, 962 individuals were surveyed in order to understand their behaviors and preferences when interacting with music streaming services. Using a stratified sampling framework, key characteristics of each persona were extracted to classify users into specific persona groups. Responses were also analyzed in relation to gender, which yielded significant differences. Our findings support the development of more targeted approaches in music services rather than a universal service model.

1. INTRODUCTION

Commercial music streaming services represent the fastest growing sector of the music recording industry. User studies from the field of Music Information Retrieval (MIR) that can be used to guide the strategic development of these streaming services as well as new methods for the navigation of large music collections have been increasing. Several studies have pointed out that the large majority of research in MIR systems has been focused on the evaluation of system accuracy and performance, creating a gap in user-centric research [19, 27, 29]. Although MIR studies are increasing in number, many tend to employ a qualitative approach and derive findings from the investigation of a limited number of users [29]. Understanding users' experiences with MIR systems, and particularly in relation to commercial music streaming services, can benefit from the adoption of more quantitative methods of analysis in addition to these qualitative assessment techniques.

This study aims to triangulate findings from prior qualitative MIR user studies adopting a quantitative approach with a larger sample to verify the findings and provide complementary insights. In particular, we conducted a follow-up study to further explore the findings of Lee and Price [18]. They presented seven different personas surrounding the use of commercial music services, derived from interviewing and observing 40 users who regularly use at least one commercial music service. Our study aims to test the applicability of the previously defined personas with a larger user population, as the results of the original study involved a relatively small sample. In this study, 962 users were surveyed in order to capture characteristics of the individuals' music listening habits based on their preferred commercial music services, and the data were analyzed in connection to the results derived from the principal study. In particular, this study seeks to elaborate on the previous findings and address the following questions:

RQ1: How similar or distinct are the seven personas when generalized to a larger stratified user sample?
RQ2: How similar or different are the persona distributions for different commercial streaming services?
RQ3: Is there a significant difference between genders with regard to their persona distribution?

2. RELEVANT WORK

2.1 Users of Music Streaming Services

The emergence of innovative music streaming services has raised the awareness and desire, both in academia and industry, for a ubiquitous system that seamlessly allows for the search, retrieval, and recommendation of music. However, a deeper understanding of the user is crucial for the development of more personalized and context-aware systems that will meet the users' needs in a wide variety of situations [27].

There have been a few studies focusing on understanding the reasons for the popularity of music steaming services such as Spotify or YouTube (e.g., [13, 21]) based on survey data or specifically measuring the quality of the music recommendations provided by commercial services such as Apple iTunes Genius (e.g., [3]). From the studies that have focused on evaluating users' experiences with music streaming services, a number of trends have emerged. Based on a large-scale survey, Lee and Waterman [20] determined an increased consumption of music on mobile devices, an increased desire for the serendipitous discovery of music and the option of customization in their listening experiences. Lee and Price [18] found that music streaming services are often perceived as "good enough" for users' purposes, and many individuals use a variety of services to accommodate needs across various contexts, illustrating Bates' "berrypicking" search behavior. A qualitative study conducted by Laplante and Downie [16] exploring the information-seeking behavior of young adults in the discovery of new music found a preference for informal channels (e.g. friends and family) as well as a distrust of experts. It was also revealed that the act of music seeking is strongly motivated by curiosity as opposed to actual information needs, which helps illustrate why browsing is an often-employed technique. Ferwerda et al. [10] explore how individuals' personality traits relate to their explicit choice of music taxonomies, and propose the creation of an interface that can adapt to users' preferred methods of music browsing. Ethnographic and observational research into music collection by Cunningham et al. [9] found that users create an implicit organization to their own music collections (digital or physical) without being fully conscious of it, and are reluctant to remove or delete songs even if they have not listened to them in months or years.

In addition, a growing number of researchers have come forward to suggest more comprehensive user models in MIR systems. Cunningham et al. [8] investigated how the factors of human movement, emotional status, and the physical environment relate to musical preferences, and based on the findings, present a model for playlist creation. In addition, assuming a mobile-based consumption of music, systems seeking to match the pace of someone in movement have also been proposed (e.g., [22, 25]). These typically aim to correlate the music played to the user's heartbeat, though most of the systems proposed would require additional context-logging hardware. A study by Baltrunas et al. [2] outlines a context-aware recommendation system for music consumption while driving by taking into account eight contextual facts including mood, road type, driving style, and traffic conditions. There have also been a few studies in which users were categorized into different types of users or personas: Celma [6] identified four different types of music listeners (i.e., savants, enthusiasts, casuals, and indifferents) representing different degrees of interest in music, and Lee and Price [18] derived seven personas, hypothetical archetypes of users representing specific goals and behavior [7], from empirical user data to help understand the different needs they have regarding the use of music services, which our study is building upon.

There is notably less research dedicated to exploring how various users search for, interact with, and listen to music digitally since the widespread growth of commercial music streaming services. This paper will elaborate on how users listen to music and interact with streaming services through the application of user personas developed in the principal study [18] in order to identify behavioral differences, preferences, and varying MIR goals.

2.2 Gender and Musical Interactions

Several researchers have studied the impact of demographic characteristics such as age [5, 15] and nationality [11, 14] on musical interactions. These studies have found that both age and cultural background prove to be significant factors in individuals' music perceptions and preferences. To a lesser extent, the influence of gender in music studies has been explored, often in the field of ethnomusicology [23, 24] and music education [1, 26]. O'Neill, a leading researcher in music and education, has found striking differences in boys' and girls' preferences for music and musical activities [26]. Her study of 153 children aged 9 to 11, explored the extent to which boys' and girls' preferences are a product of gender-stereotyped associations. She found that girls showed a significantly stronger proclivity for the piano, violin, and flute, whereas boys expressed preference for the guitar, drums, and trumpet. Also each gender had similar ideas regarding which instruments should not be played by boys or girls. The study supports the notion that gendered perspectives regarding music are developed early and could have a lasting impact on the way different genders go about seeking musical information. A few studies have focused on the general listening preferences and music processing of the two genders. Koelsch et al. [12] studied the differences between genders in the processing of music information. They discovered that early electric brain activity occurs bilaterally in females, and with right hemispheric predominance in males, supporting the claim that differences between genders in the processing of auditory information go beyond the linguistic domain. LeBlanc et al. [17] found the variables of age, country, and gender to all be significant factors in individuals' music listening preferences, but determined each of these variables to be involved in complex interactions with other variables. Though the effectiveness of the age and gender variables was confirmed, they did not perform the same way in each country, and therefore should be explored in relation to cultural context. In the context of MIR, few studies explored gender as a variable while examining the needs and behavior of music listeners. In our study, we specifically wanted to investigate whether there is a significant difference between genders with regard to their use of music streaming services, to complement what we already know about gender differences in other musical interactions.

3. STUDY DESIGN AND METHOD

3.1 Background

The principal study [18] was conducted in 2015 in order to gain insights into how users' personalities and characteristics affect their interactions with and preferences for particular MIR systems. In the study, 40 subjects participated in semi-structured interviews regarding how they evaluate music services and think-aloud sessions during which subjects described and narrated their actions as they used their preferred music service. A card sorting activity recording subjects' comments, actions, and behaviors throughout the process derived seven personas: Active Curator (AC), Addict (AD), Guided Listener (GL), Music Epicurean (ME), Music Recluse (MR), Non-Believer (NB), and Wanderer (WA). The typical behaviors and tendencies for each of these personas regarding their use of commercial music services are described in detail in [18].

3.2 Method

The online survey was developed using SurveyMonkey, an online survey tool, and responses were collected during April and May 2015, before the demise of streaming services Grooveshark and Rdio and before the release of Apple Music. The survey contained a total of 26 questions pertaining to individuals' music listening habits and behaviors, their interactions with MIR systems, and preferred music streaming services. The questions were developed in connection to the results of the principal study [18] in order to test the applicability of the seven personas with a larger user population. A majority of the survey questions and response options targeted one or more of the previously defined personas with the intention to classify a user's response to a particular persona (further discussed in Section 4.2). A limited amount of demographic information was also collected, including age and gender.

Distribution methods to recruit participants included an open call for individuals age 14 or older via University of Washington departmental listservs and posts to online message boards such as Reddit. A total of 1,028 responses were collected, of which 962 complete responses were used in the analysis. The survey responses were used to generate user profiles consisting of a list of behaviors and preferences exhibited when interacting with music streaming services. The 26 survey questions were translated into 32 variables. The data were then analyzed in RStudio and Excel environments.

4. FINDINGS AND DISCUSSION

4.1 Demographic Information

The average age of respondents was 23.4 (SD = 7.8). Sixty-one respondents did not report an age, and four respondents under the survey participation age of 14 were excluded in the analysis. The breakdown of gender distribution were as follows: 57.3% were male, 36.4% were female, 1.7% selected "other," and 4.7% did not specify their gender. 78.3% of respondents described themselves as White or Caucasian, 7.0% described themselves as Asian, 3.7% described themselves as Multiracial, 2.4% described themselves as Hispanic, and 2.2% described themselves as Black, respectively. 5.5% of respondents did not indicate or specify an ethnic affiliation. Responses were collected from 54 countries. The five countries with the most responses were: the United States (63.52%), Canada (7.1%), the United Kingdom (3.8%), Australia (2.6%), and Germany (2.1%). 5.7% of respondents did not indicate or specify a country of residence.

4.2 Filtering Method

Survey respondents were asked a series of questions regarding their music listening habits, behaviors, and actions. Questions pertaining to individuals' behavior and actions when searching for and listening to music were pivotal in determining and classifying respondents to specific personas. To classify respondents into personas, a filtering method using a combination of question-response(s) was applied to the entire sample. For each persona, if the participant selected the primary question and response pair and one of two secondary question and response pairs, he or she was classified as a respondent exhibiting that particular persona. These primary and secondary question-response pairs are summarized in Table 1.

Active Curator	Primary: Regularly curates and listens to playlists
	Secondary: Makes playlists more than once a month OR Cares about organizing collection and willing to spend time for it
Addict	Primary: Spends more time searching rather than browsing for music
	Secondary: Likes a few songs and listens to them over and over OR Most likely to listen to a song repeatedly when they hear a new song they enjoy
Guided Listener	Primary: Most likely to use a new song they like to generate recommendations of similar songs
	Secondary: Finds recommendations generated by a streaming service most appealing OR Wants to engage with a music streaming service minimally
Music Epicurean	Primary: Likely to seek out the whole album or search online to learn more about a song they like
	Secondary: Very or somewhat interested in an artist's relationship to other artists, genres, or music scenes OR Purchases music approximately once a month or more
Music Recluse	Primary: Not at all or not very likely to recommend a song to a friend
	Secondary: Listens to music they consider a "guilty pleasure" often to all the time OR Not willing or reluctant to share personal information/listening history with a streaming service
Non-Believer	Primary: Does not trust music recommendation generators and prefers finding music through other methods
	Secondary: Does not think an app or service can pick music they would like OR Does not use the social features of streaming services
Wanderer	Primary: Finds and listens to music from many sources and is always looking for something new
	Secondary: Spends more time browsing rather than searching for music OR Takes satisfaction in discovering new artists others have not heard of

Table 1. Filtering mechanism for assigning personas.

4.3 Similarity among Personas

Through the filtering method used to create sample subsets for each persona, 155 respondents (15.4%) were classified as Active Curators, 184 (18.2%) as Addicts, 47 (4.7%) as Guided Listeners, 121 (12.0%) as Music Epicureans, 119 (11.8%) as Music Recluses, 120 (11.9%) as Non-Believers, and 263 (26.1%) as Wanderers. The filtering method used to classify respondents did not return mutually exclusive results in all cases, leading to a number of respondents to be classified with multiple music personas. This is consistent with the observation of Lee and Price that "any user may exhibit a combination of these personas as they are not mutually exclusive (p. 478)" [18]. In total, 732 respondents (71.2%) were identified as exhibiting one or more personas. Of the total number of responses, 493 respondents (67.3%) were classified as exhibiting one persona, 204 respondents (27.9%) as two personas, 32 respondents (4.4%) as three personas, and only 3 respondents (0.4%) were classified as having four personas. These results suggest that enough distinctness exists between at least some of these personas that they tend to not be exhibited by the same person. At the same time, it indicates that a closer relationship exists between particular user personas than with others, and how a respondent's classification as exhibiting more than one persona may represent a fluctuating or shifting of persona association, depending on the user's momentary listening needs or context. It is noteworthy that 28.8% of respondents did not show a distinct persona; rather, they exhibited a range of different behaviors related to a number of different personas.

We calculated the Jaccard similarity coefficient to measure the similarity among personas (Table 2). This statistic represents the degree of overlap between two sets of data ranging from 0 to 1 [28]. Guided Listener and Music Recluse have the largest overlap among classified survey respondents, while the Active Curator and Wanderer, and the Addict and Wanderer have the least.

	AC	AD	GL	ME	MR	NB	WA
AC							
AD	0.61						
GL	0.73	0.68					
ME	0.66	0.58	0.77				
MR	0.67	0.67	0.79	0.69			
NB	0.67	0.67	0.78	0.69	0.76		
WA	0.43	0.43	0.63	0.61	0.54	0.55	

Table 2. Similarity among personas measured by Jaccard similarity coefficient.

We attempted to identify the reasons for these patterns by comparing these coefficient values, examining how the personas were originally defined, and reviewing the qualitative data reported in the principal study including direct user quotes. In regards to the personas with the largest overlap, the major similarity between the two is that they prefer not to engage or interact with the service very much. Guided Listener is passive and minimally invested when it comes to engagement with a music service. Music Recluse also tends to limit their engagement with the system by not actively sharing their information or using social features. The difference between these personas is that the Guided Listener trusts a music service enough to let the service select music on their behalf while the Music Recluse has little to no interest in sharing their music preferences or listening history with a music service because they are private listeners. The fact that the coefficient values between the Non-Believer and Music Recluse (0.76) and between the Guided Listener and Non-Believer (0.78) also tend to be high is noteworthy. This may be stemming from the commonality among these personas that they do not like to share their personal information although their reasons may be different (e.g., lack of interests, distrust with recommendation algorithms, privacy concerns).

When looking at personas with the least overlap and their characteristics, the level of willingness to explore and the level of engagement with their own collection seem to be the core reasons for this difference. According to the data reported in the principal study [18], the Wanderer is primarily concerned with finding new music across platforms and genres and is generally exploratory in their music listening while the Addict tends to repeatedly listen to a few songs they know and like. Also the Active Curator shows a high level of engagement with their own music collection which takes the form of playlist creation and collection organization/management whereas the Wanderer is focused on new music discovery which often occurs outside of their own collection.

4.4 Persona Classification and Preferred Services

When examining the distribution of the seven user personas across the most popular streaming services, several notable trends emerge. Personas were assigned to respondents using the filtering method described above in Section 4.2, and respondents' preferred service choice was determined using their responses to the survey question asking for the primary streaming service they use. Overall, the three most popular music streaming services selected by survey respondents were: Spotify (28.8%), YouTube (25.2%), and Pandora (17.2%). These were followed by iTunes (6.0%), SoundCloud (5.7%), and Google Play (4.2%), and several other services that were selected by less than 2% of respondents. We conducted a chi-square analysis to identify statistically significant differences between the persona distribution across the three most popular services (i.e., Spotify, YouTube, and Pandora) based on respondents' stated preference of primary streaming service.

When looking at those respondents who selected Spotify as their primary service (Figure 1), the Active Curator persona had the greatest representation with 28.1%, much more than other two services (X^2=28.37, df=2, p=0.000). Spotify includes a range of features making it easy for users to save songs for playlist creation as well as discover new music based on their listening history, which are design elements that the Active Curator would find valuable. Conversely, the Guided Listener persona was under-represented in its indications of a preference for Spotify, as the service itself requires a certain amount of curation to take advantage of its features (e.g. making an account, importing one's library, and understanding the robust interface) that the user is presented with upon first interacting with the service. For the less engaged personas, the initial process of familiarizing oneself with Spotify may not be worth the effort.

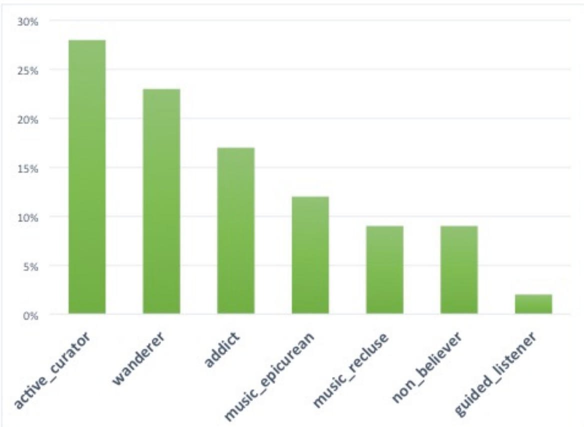

Figure 1. Persona distribution of Spotify users.

For those respondents who selected YouTube as their primary service (Figure 2), the Addict persona had the greatest representation with 24.1%, significantly different from other services (X^2=13.40, df=2, p=0.001). Given that YouTube is an ideal platform for known-item searches, and allows for the easy replay of videos and songs, in the context of the Addict persona's user needs, YouTube would appear to be a realistic primary service choice. Music Epicureans were also most likely to choose YouTube as their primary service. The staggering amount of content, including concert footage, interviews, and rare tracks, often not available on any other services, allows for the endless discovery of new musical content. The ability to navigate through an extensive range of content is an appealing quality of the service for even the Non-Believer, which, although a small sample of the survey, was most likely to choose YouTube as their primary service. Conversely, the heavily self-directed nature of YouTube is an unattractive option to the Guided Listener, who was the least likely of any persona to choose YouTube as their preferred service.

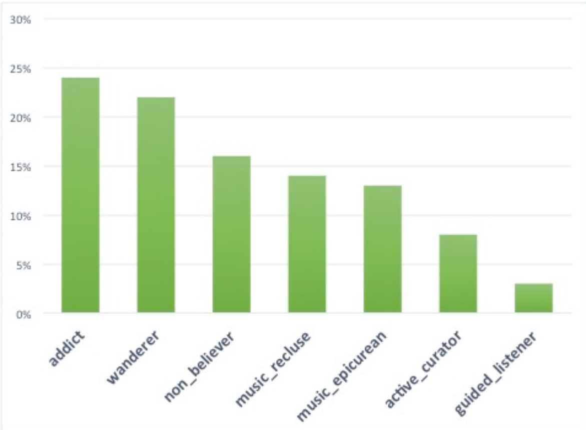

Figure 2. Persona distribution of YouTube users.

For those respondents who selected Pandora as their primary service (Figure 3), the Wanderer persona had the greatest representation with 29.7% (X^2=1.01, df=2, p=0.601), although the difference with the other two services was not significant. The most notable difference was the proportion of Guided Listeners (X^2=25.17, df=2, p=0.000). Overall, Guided Listeners were an underrepresented group in the sample, comprising only 4.7% of our population. While the respondents classified as Guided Listeners represented only 13.3% of those individuals that indicated Pandora as their preferred music service, Pandora was the primary service selected by Guided Listeners at 46.8%. Compared with other music services, Pandora provides a limited number of user features and will recommend and play content closely aligned to the user's "seed" artists. The user may be less likely to discover new or unexpected songs or artists but will also not have to interact with the service extensively during use. Because of these characteristics, Lee and Price [18] also expected that the Guided Listener persona would be the majority persona for Pandora which was indeed the case.

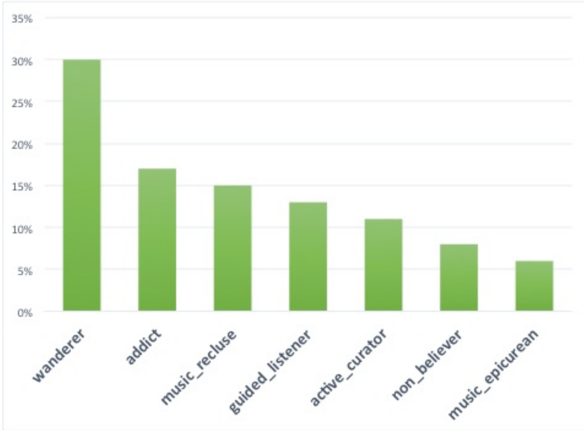

Figure 3. Persona distribution of Pandora users.

4.5 Gender Differences

Chi-squared tests revealed statistically significant differences in the way that users of different genders categorize their interactions with music services. When asked to indicate behaviors that described their music listening habits (X^2=30.40, df=4, p=0.000), 31.4% of males said they liked to listen to an album from start to finish, as opposed to only 16.4% of females. Females, on the other hand, were more likely to say that they enjoy listening to songs and artists from many different sources and are always looking for something new (32.6% for F, 30.7% for M). When asked what they typically do after hearing a new song that they enjoy (X^2=14.48, df=4, p=0.006), males were most likely to answer that they seek out the album the song came from (23.7% for F, 32.4% for M), while females were most likely to respond that they listen to the song over and over (34.1% for F; 23.5% for M).

Participants were also asked whether they find themselves more often searching or browsing for music (X^2=12.35, df=2, p=0.002); 48.9% of females identified themselves as known-item searchers and an equal share of 25.5% identified themselves as browsers and as spending equal amounts of time both searching and browsing. On the other hand, males' responses were more evenly distributed; 37.6% identified themselves as searchers, 33% browsers, and 29.4% responded that they spend approximately equal amounts of time doing both.

The tendency of females to identify as searchers is reflected in the classification of the Addict persona, which frequently relies on known-item searching in music seeking, encompassing 22.1% of females versus 15.8% of males (X^2=6.23, df=1, p=0.013). Females also more often identified as Music Recluse (X^2=5.16, df=1, p=0.023). The higher percentage of male browsers as opposed to female browsers supports the gender distribution of the Music Epicurean (8.9% for F, 14.6% for M; X^2=7.01, df=1, p=0.008) and Non-Believer (7.4% for F, 14.7% for M; X^2=12.28, df=1, p=0.000) personas. Table 3 shows the overall distribution of personas by gender. This pattern of males as the more exploratory gender in their music-seeking behavior is also exhibited in the breakdown of preferred music services. When asked to indicate their most preferred service, the top three services (Spotify, YouTube, and Pandora) accounted for 67.8% of males' top selection, whereas 77.6% of females named one of these top three services as their most preferred one. Overall, males selected 18 different options, while females chose 14.

Persona	Female		Male		X^2	*df*	*p*
Active Curator	69	17.5%	82	14.2%	1.94	1	0.163
Addict	87	22.1%	91	15.8%	6.23	1	0.013
Guided Listener	20	5.1%	24	4.2%	0.46	1	0.499
Music Epicurean	35	8.9%	84	14.6%	7.01	1	0.008
Music Recluse	57	14.5%	56	9.7%	5.16	1	0.023
Non-Believer	29	7.4%	85	14.7%	12.28	1	0.000
Wanderer	97	24.6%	155	26.9%	0.61	1	0.433
Total	394	100.0%	577	100.0%	-	-	-

Table 3. Persona distribution by gender.

Overall, males seem to exhibit more exploratory nature in their music discovery endeavors. When participants were asked whether they take satisfaction in finding or discovering new artists that few people are aware of, 78% of males answered affirmatively versus 67.9% of females (X^2=12.16, *df*=1, *p*=0.000). Males also indicated that they more frequently curate playlists, with 33.9% of males saying that they like to make playlists at least once a week, compared to 23.9% of females (X^2=11.06, *df*=3, *p*=0.011). Males were also more likely to claim that listening to music occupies their full attention (14.2% for F, 21.2% for M; X^2=7.55, *df*=1, *p*=0.006).

These findings suggest that it may be fruitful for developers of commercial music streaming services to consider gender-specific approaches in the design and function of system features. Services targeted at males should account for the desire of discovering novel musical content, including robust features that consistently stimulate the encounter of unfamiliar artists and songs. Females are more likely to require features that allow for the easy replayability of content and support passive engagement.

There are also some notable similarities across genders. Neither males nor females tend to care much about the organization of their music collections. Of the respondents, 43.5% of males and 42.2% of females responded that they care only a little and are willing to spend minimal time organizing their collections (X^2=33.58, *df*=3, *p*=0.000). Additionally, both males (41.8%) and females (44.1%) responded that they prefer to get recommendations from those with similar tastes or listening habits rather than friends, family, music experts and curators, or streaming services (X^2=21.80, *df*=5, *p*=0.000). Therefore, services should incorporate measures of user profile and listening history similarity as a prominent feature for music recommendation. Interestingly, of all the respondents, 78.3% said that they were either somewhat likely or very likely to recommend a song or artist to a friend they thought would like it, but a mere 8.8% of all respondents said that they typically use the social features provided by a streaming service. The lack of use of social features was consistent across both genders (91.4% for F, 90.4% for M; X^2=0.059, *df*=1, *p*=0.808). This indicates that while users want to share music discoveries or new artists, they prefer to do so through channels not associated with the streaming service itself. This represents a potential area of innovation for commercial streaming services in evaluating how they incorporate social features into their platforms.

5. CONCLUSION AND FUTURE WORK

By testing the applicability of personas with a larger stratified user sample, we were able to determine the relative uniqueness of some personas and the closeness of others. In calculating the Jaccard coefficient, we found the Active Curator and Wanderer, and Addict and Wanderer personas to be the most dissimilar, while the Guided Listener and Music Recluse personas had the most overlap among the survey respondents. Going forward, we may consider reevaluating those less distinctive personas by further examining the overlapping characteristics of each, and redefine them accordingly.

When looking at the persona distributions for major commercial streaming services, patterns emerged between users' classified personas and their preferred services. While Spotify tends to draw in a high representation of more engaged personas like the Active Curator, it seemingly repels others, such as the Guided Listener persona. Similarly, YouTube, the service most preferred by Music Epicureans, was not popular among Guided Listeners, who instead prefer the more self-guided service, Pandora.

A further breakdown revealed significant differences between genders with regard to their persona distribution and preferred services. While the classification of the Addict persona skewed female, the Music Epicurean persona was male skewed. The Music Recluse and Non-Believer personas were also significantly different, with males more often identifying with the Non-Believer persona, and females comprising a higher representation of the Music Recluse persona. In regards to the preferred service distribution, a significant proportion of males and females reported Spotify and YouTube as their most preferred services. However, it was found that females are much more likely to favor Pandora, while males more often opt for peripheral services, such as Google Play and SoundCloud. The significant differences found between male and female users' preferences, characteristics, and expectations of music services suggest a need for further research. Future work will focus on obtaining a deeper understanding of the reasons for these gender differences and behaviors when engaging with music streaming services.

A revised model may be developed for classifying respondents to the defined user personas, incorporating the self-reported persona classification data from users. Asking users to identify themselves by the sets of traits represented by personas may help us further verify the validity of our filtering mechanism. In addition, further investigation through a qualitative study should be conducted to investigate those individuals that are classified into more than one persona to determine the factors at play, such as shifts across different contexts.

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