Filter Bubbles And Music Streaming: 
The Influence of Personalization And 
Recommendation Algorithms on Music Discovery Via 
Streaming Platforms

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“But what makes music special - what makes it special for identity - is that it defines a space without boundaries (a game without frontiers). Music is thus the cultural form best able both to cross borders - sounds carry across fences and walls and oceans, across classes, races and nations - and to define places; in clubs, scenes, and raves, listening on headphones, radio and in the concert hall, we are only where the music takes us.” -Simon Frith, 1996
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Introduction

Modern technologies allow an incredible amount of music to be globally available. Theoretically, this should result in inevitable exposure to music from various cultures. However, the highly personalized natures of media platforms seem to limit this exposure. Music streaming sites such as Pandora and Spotify boast that their algorithms cater to the existing interests of users. I offer that these personalization algorithms create filter bubbles, which occur when a user is repeatedly exposed to information that falls under his or her existing interests, needs, and beliefs (Flaxman, Seth, Goel, and Rao, 2016; Pariser, 2011). As a result, the listener is primarily exposed to music that they would listen to anyways. Similar to algorithms that manage social media news feeds, I assume that streaming algorithms recommend songs to users based on what they like, what their friends like, and what their demographic likes. The use of streaming services, therefore, may influence how users find and collect new music--particularly when such music is outside their normal realm of listening.

Central Research Question: How do streaming algorithms influence the way that users discover and appreciate diverse music?

Hypothesis: I hypothesize that the process of creating algorithms that cater to each individual creates filter bubbles in music media platforms, which could limit user exposure to diverse music.
Clarifications And Definitions:

“Streaming services” are online platforms that allow users to search for songs and play them immediately, rather than buying or saving them to a hard drive. Throughout this paper, I refer to “streaming algorithms” as the code that such services use when personalizing the user’s streaming experience by recommending songs or curating playlists. For the purpose of this study, “diverse music” is a characteristic used to denote songs with qualities that differ from those that the users already listen to regularly. Because there is an endless list of such features, my research focuses only on characteristics that are influenced by culture and location. These traits can be identified by language, genre, and the artists involved.

Approach:

To address my research question, I constructed a survey on music streaming habits (with an emphasis on discovery). The “Results” chapter of this paper includes several analyses of the survey results. I examine how the survey respondents searched for, encountered, and reacted to new or unfamiliar artists. I also compare how respondents of various language backgrounds searched for, encountered, and reacted to non-English songs. This data allows me to draw observations regarding how users engage with discovery on streaming platforms.

Research Significance:

Streaming service subscriptions are the recorded music industry’s fastest growing revenue source (IFPI, 2015 ; 2016 ; 2017) and may be displacing conventional music discovery methods (Dewan and Ramaprasad, 2014 ; Greasley and Lamont, 2006 ; Lindsay, 2016 ; Nag,
The widespread use and growing importance of streaming services indicate that scholars should examine the implications of streaming services just as they are analyzing the effects of social media.

If music media platforms indeed resemble filter bubbles, then music users may not be as encouraged to discover music that is different from their current tastes. This can become an issue, because listening to music is one activity that allows people to develop empathy for other perspectives (Taramigkou et al., 2013). Cultural goods are one of the primary factors that integrate individuals into social structures, and listening to music is an inclusive way to develop cultural knowledge (Lizardo, 2006). In discussing cultural bridges and fences, Omar Lizardo notes that cultural pursuits with a steep learning curve—such as “acquired tastes” or sports that need extensive training—are more likely to be used as a fence that excludes individuals from a culture (2006). However, popular cultural forms such as music can serve as a bridge to connect people, because listening to music can require minimal integration and acquired knowledge (Lizardo, 2006). Furthermore, the likelihood that a popular art form such as music will be selected as a topic of conversation between two individuals is inversely proportional to the strength of the tie between those individuals (Lizardo, 2006). Therefore, if people do not know another well, they are more likely to drift towards a song that they all know when they converse. Other scholars, like Simon Frith, mention that popular songs are more accessible between people of different cultures. In responding to a song, people may draw emotional alliances with the performer and the other fans of the performer (Frith, 1996: 121).

While the possible implications of music on cultural learning provide significant rationale to examine filter bubbles in music streaming, there is perhaps an even stronger argument for
studying the effects of streaming code: the extreme opacity of personalization and recommendation algorithms. Streaming users do not know why or how they are being shown certain songs, artists, and genres. They may not understand the extent to which their streaming service dictates their music taste. As Cathy O’Neil mentions in *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*, this opacity can turn harmless algorithms into destructive ones that further discrimination (2017). Therefore, studies like this paper contribute to a growing amount of information that pulls the curtain back and promotes a more transparent environment regarding media use.
The literature review outlines existing knowledge, data, and relevant information to supplement the research conducted and analyzed in this paper. This review covers prior research on the following: (1) the existence of filter bubbles and echo chambers, (2) the extent to which filter bubbles positively or negatively influence users, (3) data compilation and targeted advertisements via music streaming platforms, (4) music consumption in the age of streaming, and (5) music discovery as a tool for empathy and identity.

Filter Bubbles And Echo Chambers

With the rise of information technology and hyper personalization, scholars have studied the idea of a filter bubble and how it affects media users. Eli Pariser explains that prediction engines constantly analyze a user’s habits in order to continually build a narrative of who that user is, what they want, and what they’ll do next (2011: 9). As a result, each user’s experiences and interactions take place within their own bubble of catered information. While people have always consumed media that appealed to their interests to some extent, filter bubbles introduce new dynamics--the user is alone in this bubble, they do not choose to enter it, and they do not know why they are seeing one type of content instead of others (Pariser, 2011). Perhaps the most concerning quality of filter bubbles is that many users do not know that they are in one (Pariser, 2011).
This bubble is a result of machine-learning models such as adaptive user interfaces (AUI’s). These models allow algorithms to morph a system and recommend content based on what is relevant and agreeable to the user (Flaxman, Goel, and Rao, 2016; Schneider-Hufschmidt, Kūme, & Malinowski, 1993). For example, if someone searches something on Google and clicks the second link available, Google then uses that “click signal” as an indicator that the second link is more relevant to the searcher than the first (Pariser, 2011). Google’s algorithms use cues such as click signals to assume a host of preferences and characteristics that a user has, such as their political party identification or the age of their children. These cues help Google curate the user’s experience by showing them links that are more relevant to their life situation. Another case is Amazon-- if someone has spent the day reading their Kindle at the beach, Amazon can subtly customize its site to appeal to what that user has read (Pariser, 2011). Facebook also uses similar models. In response to increasingly crowded Facebook feeds, Facebook started to use the algorithm EdgeRank to power the Top News Feed (Pariser, 2011). EdgeRank ranks every interaction on Facebook by affinity, content weight, and time (Pariser, 2011). EdgeRank uses that information to determine what is relevant to the user, and then organizes what the user sees on their news feed accordingly.

By showing users exactly what they would want to see, filter bubbles can amplify segregation based on ideologies, preferences, and characteristics (Flaxman, Goel, and Rao, 2016). Users find themselves in “echo chambers,” in which they are largely exposed to conforming opinions (Flaxman, Goel, and Rao, 2016). While filter bubbles and echo chambers are similar, they differ in that a filter bubble is a “cultural and ideological bubble in which an individual continues to see, listen and read what reinforces its opinions and interests,” whereas
an echo chamber is “a group situation where established information, ideas, and beliefs are uncritically spread and amplified, while dissenting views are ignored” (Reviglio, 2017: 283). Filter bubbles occur without the autonomy of the user, whereas echo chambers occur when people engage in selective exposure and homophily--therefore, while echo chambers existed before the digital age, filter bubbles as we know them did not (Reviglio, 2017).

**Disagreements Regarding The Influence of Filter Bubbles**

There are competing claims among scholars regarding whether or not the negative effects of filter bubbles outweigh the positive ones (Flaxman, Goel, and Rao, 2016 ; Reviglio 2017). Some scholars claim that filter bubbles are generally positive and that AUI’s increase the user’s exposure to diverse perspectives (Benkler, 2006 ; Obendorf et al., 2007 ; Goel, Mason, and Watts, 2010 ; Goel, Hofman, and Sirer, 2012 ; Messing and Westwood, 2012). Kartik Hosanagar and his colleagues found that personalized music recommendation systems could actually increase within-user diversity (2013). Other scholars have found evidence that filter bubbles have neither negative nor positive effects (Flaxman, Goel, and Rao, 2016 ; Borgeisus et al., 2016).

Still, various studies find that filter bubbles could limit diversity (Tintarev, 2017 ; Reviglio 2017). Scholars such as Nava Tintarev and Urbano Reviglio claim that filter bubbles can restrict personal creativity, insight, learning, and the ability to build productive social capital. They, among others, suggest that filter bubbles can make users more vulnerable to censorship, propaganda, polarization, misinformation, and conspiracy theories (Reviglio 2017 ; Keegan, 2016; DiFranzo and Gloria-Garcia, 2017 ; Groshek and Koc-Michalska, 2017). Lastly, Reviglio
claims that filter bubbles put digitally literate users at an advantage, because they acknowledge the existence of filter bubbles and can actively search for more diverse content whereas others may not know how to find such content (2017).

**Data Compilation And Targeted Advertisements via Music Streaming Platforms**

As mentioned earlier, machine learning models can collect data about digital media users in multiple ways and use that data to better curate the user’s experience. This data is also stored, shared, and sold to external groups such as online advertisers, who use this data to target specific customers. While a tech-savvy consumer may realize that platforms like Google or Facebook have personal information about them, general awareness around the personal data stored by music platforms is less widespread. A multi-year data and research partnership between GroupM and Spotify revealed that the future of music streaming has millions of dollars to gain from online advertising (Kaye, 2016). People often dictate a “mood” or “moment” when they are streaming, because they choose playlists specifically made for activities such as being at the gym, taking a shower, or cooking dinner. GroupM revealed that this data will account for $220 million in new advertising revenue for Spotify in multiple markets (Kaye, 2016).

The use of streaming for advertising is not only occurring in the United States. China, for example, is one region in which various brands have launched advertising partnerships with streaming platforms. McKinsey & Company’s analysis of music streaming in Asia revealed some of these partnerships (Bundgaard, Karlsson, Lau, and Pereira, 2016):
While all of these partnering companies may not have acquired personal user data, they can still target specific users based on their music streaming habits. The partnership between Nike and Spotify was particularly interesting, given that Spotify’s playlist analyzer algorithm told the users what items they were most suited to. In this way, the streaming platform was dictating the style choices of users.

### Music Consumption in The Digital Age

The emergence of digital media has greatly influenced music. It has resulted in an unlimited abundance of available tracks, as well as low barriers of entry for listening, discovering, and sharing music (Greasley and Lamont, 2006; Nag, 2017). While freedom of choice is embraced in this environment, scholars have found that consumers are often overwhelmed and left craving scarcity (Nag, 2017). Damon Centola, Juan Gonzalez-Avella, and Victor Eguiluz claim that a sudden flood of cultural options can cause a cultural group to
disappear, because there are not enough options that limit diversity (2007). This idea would suggest that streaming sites—which could certainly be said to offer a “sudden flood of options”--actually limit the user’s desire for diversity, as the user is overwhelmed by an incredible amount of diverse music. Streaming services seem to notice this need for scarcity and cater to users accordingly. Jeremy Morris and Devon Powers argue that while branded musical experiences by streaming services appear to offer fluid and abundant musical content, these platforms actually “create circumscribed tiers of content access for a variety of scenarios, users and listening environments” (2015: 1). Streaming environments therefore push users to consume available goods in a networked way, largely connected to social structures (Lizardo, 2006).

Choosing which music to consume based on a social structure can initiate feelings of belonging and give the user a sense of social homophily.¹ Some scholars have found that social awareness strongly influences whether users share music and follow others in the digital age (Hagen and Lüder, 2016). This awareness is based on socio-demographic, behavioral, and intrapersonal characteristics (McPherson et al., 2001). Indeed, music preferences often suggest lifestyle choices, indicate friendship formation, and provide a means for discriminating between social groups (North and Hargreaves, 2007; Selfhout, Branje, ter Bogt, and Meeus, 2009).

The claim that tastes are socially conditioned was established before the Internet’s existence, particularly through the work of Pierre Bourdieu (1984). Building on Bourdieu’s arguments, Centola, Gonzalez-Avella, and Eguiluz found that homophily can sometimes produce cultural groups whose members cannot interact across group boundaries because each group is

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¹ Homophily is the tendency of people with similar traits (including physical, cultural, and attitudinal characteristics) to interact with one another more than with people with dissimilar traits. (Centola, Gonzalez-Avella, and Eguiluz, 2007: 905). It can influence the information that people receive, the attitudes they form, and the interactions that they experience (McPherson, Smith-Lovin, and Cook, 2001).
so different from one another (2007). These scholars also found that the excess of options available to someone may prohibit them from forming group identifications or long-term social ties (2007). Therefore, even though homophily exists on streaming sites, it may be difficult for users to assume permanent group identities and music preferences.

**Music Discovery as a Tool For Empathy And Identity**

As mentioned above, scholars have found that mass media can affect the emergence of cultural diversity. Music is a particularly interesting tool for interaction with diversity because of its emphasis on discovery. While recommendations from streaming platforms can help users sort through the enormous amount of music available, the act of individual music exploration allows users to understand the world from a different perspective, expand their interests, explore new or divergent music, and identify serendipitous content (Taramigkou et al., 2013). This process of music discovery encourages users to develop empathy\(^2\) by extending beyond their personal views and experiencing other perspectives in an intimate way (Lizardo, 2006; Taramigkou et al. 2013).

Just as music discovery can lead to empathy, it can also aid in identity formation. Thomas Turino nicely explains the connection between music and identity formation:

“Identity is comprised of what we know best about our relations to self, others, and the world, and yet is often constituted of the things we are least able to talk about...The crucial link between identity formation and arts like music lies in the specific semiotic character of these activities which make them particularly affective and direct ways of knowing.” (1999: 221).

\(^2\) Empathy is “the action of understanding, being aware of, being sensitive to, and vicariously experiencing the feelings, thoughts, and experience of another of either the past or present without having the feelings, thoughts, and experience fully communicated in an objectively explicit manner” (Merriam-Webster).
Indeed, music discovery is often personal. Similarly, music-streaming services are regularly explored in private situations, and they can be used to store personally meaningful music compilations.

**Literature Discussion**

Evidently, research has been done on the influence of filter bubbles and how they affect media interactions. Scholars have also studied music consumption in the digital age (to an extent) and the use of music discovery as a tool for empathy and identity. Still, little research thus far draws connections between filter bubbles and music personalization algorithms to analyze the effects they may have on cultural learning and diversity discovery. This paper attempts to address these gaps in research by providing more insight into how streaming algorithms influence the listener’s discovery experience on music platforms, as well as the implications on encountering and adopting diverse music that result from these digital discovery habits.
Methods

As previously stated, my research addresses the influence that streaming algorithms have on how users discover and appreciate diverse music. I initially hypothesized that personalized recommendation algorithms create filter bubbles in music media platforms and that these filter bubbles limit exposure to diverse music.

I constructed a survey with several discovery-related questions that centered around interactions with new artists or non-English songs. For the purposes of the survey, “new artist” was a term used to describe any artist that the survey respondents were unfamiliar with on the streaming service. I used language as a discovery factor to get an idea of the cultural learning—or lack thereof—that happens as a result of streaming algorithms. Different countries and cultures speak different languages; therefore, by analyzing how English speakers are encountering and/or interacting with non-English songs on streaming platforms, I could draw observations regarding the prevalence of social homophily and cultural diversity on those services.

The survey was taken by 101 people, aged 18 - 55, who were fairly educated (have pursued or are pursuing a bachelor’s degree or higher) and use streaming services. The majority of respondents (88 out of 101) were between 18 and 25 years of age, four were between 26 and 35 years of age, one was between 36 and 45 years of age, and eight were between 46 and 55 years of age. 61 respondents identified as she/her, 37 respondents identified as he/him, and three respondents identified as they/them. All survey respondents spoke English, but not all lived in the United States. 90% of the respondents spoke English as their first language, 10% spoke a first
language other than English, and 60% of the respondents spoke at least two languages conversationally.

Participants were recruited to take the survey through email and social media outreach. In order to take the survey, the participants needed to be at least 18 years of age. Before taking the survey, all participants read and signed an IRB approved information sheet. Participants had the option of including their email address to be entered in a raffle for a $20 Amazon gift card, but these email addresses were kept separately from the data to ensure participant anonymity. The raffle was completed after the survey closed in March of 2017.
Results and Analysis

This chapter includes my results from the survey. It is comprised of several sections, each with multiple figures and analyses. The sections are as follows: (1) general findings about the music media habits of survey participants, (2) findings regarding the music discovery habits of survey participants, and (3) findings regarding the music discovery habits of survey participants who have interacted with foreign languages throughout their lives. Most tables and figures are included in this section for reference. Additional figures can be found at the end of this paper, in the section titled “Figures.”

All of my results are only in relation to the 101 participants that I surveyed. I am not claiming that a random population would act exactly like these participants, as I did not perform regressions or hypothesis testing. My observations are therefore only supplemented by these survey results and existing literature--I am not extending these observations to a population at large.
Section One: General Findings

FIGURE 1:

<table>
<thead>
<tr>
<th>Streaming Services Used</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandcamp</td>
<td>1</td>
</tr>
<tr>
<td>Napster</td>
<td>1</td>
</tr>
<tr>
<td>iTunes Radio</td>
<td>1</td>
</tr>
<tr>
<td>Amazon</td>
<td>7.9</td>
</tr>
<tr>
<td>Soundcloud</td>
<td>10.9</td>
</tr>
<tr>
<td>Apple Music</td>
<td>18.8</td>
</tr>
<tr>
<td>Pandora</td>
<td>20.8</td>
</tr>
<tr>
<td>YouTube</td>
<td>38.6</td>
</tr>
<tr>
<td>Spotify</td>
<td>84.2</td>
</tr>
</tbody>
</table>

Table 1: How Many Hours Per Week Spent on The Service

<table>
<thead>
<tr>
<th>Hours Per Week</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than 3</td>
<td>12.9</td>
</tr>
<tr>
<td>3-6</td>
<td>23.8</td>
</tr>
<tr>
<td>6-9</td>
<td>19.8</td>
</tr>
<tr>
<td>9-12</td>
<td>12.9</td>
</tr>
<tr>
<td>12-15</td>
<td>8.9</td>
</tr>
<tr>
<td>12+</td>
<td>21.8</td>
</tr>
</tbody>
</table>

Table 2: How Users Interact With The Service

<table>
<thead>
<tr>
<th>Interaction</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>I use playlists recommended for me by the service</td>
<td>66</td>
</tr>
<tr>
<td>I search for music and make my own playlists</td>
<td>86</td>
</tr>
<tr>
<td>I follow friends and listen to playlists that they follow</td>
<td>39</td>
</tr>
<tr>
<td>I browse by topic (mood, genre, etc) and choose playlists</td>
<td>67</td>
</tr>
</tbody>
</table>
In the survey, I left the word “genre” up for interpretation. Music listeners generally accept this term to signify a category of music (Merriam-Webster). Therefore, different genres are typically thought of as different categories of composition.

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3 In the survey, I left the word “genre” up for interpretation. Music listeners generally accept this term to signify a category of music (Merriam-Webster). Therefore, different genres are typically thought of as different categories of composition.
Several participants used more than one streaming service. Spotify was widely accepted as the preferred streaming service (Figure 1). Youtube, Pandora, and Apple Music were also popular, but no participants used Google Play (Figure 1). Table 1 indicates that participants spent varied amounts of time on streaming services per week, with the most popular time frames for weekly listening being either 3-6 or 15+ hours per week. This finding is rather interesting, as it suggests that two large groups of respondents were on different sides of a music consumption spectrum. While my data indicates that the ages of participants in these two groups did not vary much, a study done with more people in different age ranges could illuminate whether age is an influencing factor for frequency of music consumption.

Table 2 shows that 86% percent of participants searched for music actively and made their own playlists while on streaming sites. While this discovery alone could indicate that users do not merely abide by personalized recommendations, I also found that 66% of the participants used playlists recommended for them by the service, and 67% browsed playlists by topic (Table 2). These findings could suggest that the users who claimed to actively search for music may have used recommended or curated playlists to discover songs.

The majority (61%) of participants listened to 2-4 different genres for every three hours that they spent on a streaming service (Figure 2). However, the participants rarely followed new accounts, playlists, or stations (Figure 3). This occurrence suggests that users would usually rather browse and temporarily collect new music than make the commitment to follow or actually keep the music. These habits would align with Centola, Gonzalez-Avella, and Egiluz’s research, which finds that users with limitless options often lose their ability to form long-term group identifications and preferences (2007).
Section Two: Music Discovery Habits of The Entire Cohort

FIGURE 4:

FREQUENCY OF SEARCHING FOR NEW ARTISTS

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Have never searched for a new artist</td>
<td>3</td>
</tr>
<tr>
<td>Rarely ever search for new artists</td>
<td>52</td>
</tr>
<tr>
<td>1-2 new artists every 3 hours</td>
<td>35.7</td>
</tr>
<tr>
<td>1-2 new artists every hour</td>
<td>6.1</td>
</tr>
<tr>
<td>More than 2 new artists every hour</td>
<td>3.1</td>
</tr>
</tbody>
</table>

FIGURE 5:

FREQUENCY OF ENCOUNTERING NEW ARTISTS

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Have never encountered a new artist</td>
<td>1</td>
</tr>
<tr>
<td>Rarely ever encounter new artists</td>
<td>26</td>
</tr>
<tr>
<td>1-2 new artists every 3 hours</td>
<td>42</td>
</tr>
<tr>
<td>1-2 new artists every hour</td>
<td>19</td>
</tr>
<tr>
<td>More than 2 new artists every hour</td>
<td>12</td>
</tr>
</tbody>
</table>
Participants were asked how often they purposefully searched for artists that they were unfamiliar with on the streaming service, or “new artists” (Figure 4). Almost all of the participants (97%) had searched for a new artist at least once, but over half of the respondents (52%) rarely ever searched for new artists (Figure 4). This finding is particularly interesting, given that 86% of the participants claimed to regularly search for music and make their own playlists (Table 2). This could suggest that participants are “searching” for music by looking at pre-made playlists or typing in the names of artists and songs that they already know, as opposed to actively looking for new artists. While these participants rarely ever searched for new artists, 42% of respondents spontaneously encountered one to two new artists for every three hours they

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4 These reactions range on a spectrum from least to most pleased. I did not explicitly define these reactions on the survey, as they are commonly known emotions in the English language. According to Merriam-Webster: Angry = Having a strong feeling of displeasure and usually of antagonism Annoyed = Having a feeling of irritation Neutral = Not expressing strong opinions or feelings Amused = Feeling pleasantly entertained or diverted Excited = Having a heightened state of energy, enthusiasm, and/or eagerness
spent streaming, and 12% spontaneously encountered more than two new artists every hour (Figure 5). This could suggest that curated playlists occasionally provide users with new artists.

As the figures indicate, a majority of participants rarely ever searched for new artists, and yet many seemed to encounter new artists anyways. When they spontaneously encountered new artists, the most popular reaction among participants was excitement (37%) or neutrality (33%) (Figure 6). 21% were amused when they encountered new artists, and 9% were annoyed (Figure 6). This suggests that while the participants do not search for new artists regularly, they tend to react positively or neutrally when they do encounter new artists without purposefully engaging in discovery. Scholars have indeed found that people like to achieve a feeling of randomness and spontaneity on streaming sites, though they often do not attain this by encountering new music--instead, they self-regulate on streaming systems by shuffling songs on their existing playlists (Greasley and Lamont, 2006).

FIGURE 7:
FIGURE 8:

FREQUENCY OF ENCOUNTERING NON-ENGLISH SONGS

- Have never encountered a non-English song: 12.9%
- Rarely ever encounter a non-English song: 57.4%
- 1-2 songs every 3 hours: 18.8%
- 1-2 songs every hour: 5.9%
- More than 2 songs every hour: 5%

FIGURE 9:

REACTION TO SPONTANEOUSLY ENCOUNTERING A NON-ENGLISH SONG

- Excited: 26.7%
- Amused: 18.8%
- Neutral: 45.5%
- Annoyed: 8.9%
- Angry: 0%
Participants were also asked questions about discovery based on song language. Similar to the proportion of participants who rarely searched for new artists, 51.5% of participants rarely searched for non-English songs (Figure 7). However, unlike the results for encountering new artists--where 26% rarely spontaneously encountered new artists and 42% encountered one or two new artists for every three hours they spent streaming--the majority of participants rarely spontaneously encountered non-English songs (57.4%), and only 18.8% of participants encountered one to two non-English songs for every three hours spent streaming (Figure 8). Furthermore, while the popular reaction to spontaneously finding a new artist among participants was excitement, the popular reaction to spontaneously finding a non-English song was neutrality (45.5%) (Figure 9). Still, participants were more likely to be excited and amused when finding a non-English song than annoyed--8.9% of respondents were annoyed when they came across a non-English song, which is similar to the 9% of respondents who were annoyed when they encountered a new artist (Figure 9).

**Section Three: Music Discovery Habits of Participants With Various Exposure to Foreign Language in Their Everyday Lives**

After examining the general findings per question, I split the anonymous participants into language groups based on their self-reported language experiences - 41 participants only spoke English, and 60 participants spoke at least two languages. I formed these groups to get a better idea of language exposure across streaming services. I wanted to see if people who grew up speaking multiple languages and observing different cultures were more likely to encounter
different kinds of music than those who had only been exposed to the English language and American culture.

For these results, I provide charts of comparison between the groups and refer to more specific charts which can be found at the end of this paper. While I am mostly comparing those who speak only English and those who speak multiple languages, I also created a line of reference in each chart for the participants who had a first language other than English (11 out of the 60 who speak multiple languages). This group is represented by a grey line, and it is crucial to acknowledge that this group overlaps with those who speak at least two languages. Therefore, comparisons cannot be made between this group and the group who speaks multiple languages. The data for this group is provided to serve as an additional comparison with the participants who only speak English.

FIGURE 13:
When asked about searching for non-English songs on streaming services, a majority (63.4%) of the participants who only spoke English reported to rarely ever search for a non-English song (Figure 12). In contrast, only 43.3% participants who spoke at least two languages and 36.3% of participants who had a first language other than English rarely searched for a non-English song (Figure 10; Figure 11). Participants who spoke a first language other than English were most likely to search for more than two non-English songs every hour (18.2%) (Figure 10). 10% of participants who spoke at least two languages searched for more than two non-English songs per hour, and none of the English-only participants searched for more than two non-English songs per hour (Figure 11; Figure 12). English-only participants were most likely to have never searched for a non-English song (26.8%), while 5% of participants who spoke at least two languages had never searched for a non-English song (Figure 11; Figure 12). All of the participants who had a first language other than English had searched for a non-English song before (Figure 10).

These results are perhaps unsurprising, as people who have been exposed to different languages and understand those languages would reasonably be more likely to seek out songs in those languages. Similarly, people who only speak one language (in this case, English) could be reasonably expected to mostly search for songs in their native--and only--language.
2.4% of the participants who only spoke English encountered more than two non-English songs every hour, while 6.7% of the participants who spoke at least two languages encountered more than two non-English songs per hour (Figure 15; Figure 16). 2.4% of the participants who only spoke English and 8.3% of the participants who spoke at least two languages encountered one to two songs every hour (Figure 15; Figure 16). 24.4% of the participants who only spoke English had never encountered a non-English song, while only 5% of the participants who spoke at least two languages had never encountered a non-English song (Figure 15; Figure 16). All of the participants who had a first language other than English had encountered at least one non-English song (Figure 14). These results suggest that people who do not search for songs in
foreign languages are less likely to encounter them spontaneously. This could contribute to the idea that personalization algorithms show users songs based on their perceived likes and background.

FIGURE 21:

The participants most likely to be excited when they encountered a non-English song were the ones who only spoke English (48%) (Figure 20). 31.7% of participants who spoke at least two languages were excited when they encountered non-English songs (Figure 18). Of those participants, the ones who had a first language other than English were less excited when they encountered non-English songs (27%) (Figure 19). Participants who spoke at least two languages were more likely to react neutrally when encountering a non-English song (41.7%)
compared to English-only speakers (29.2%), and those with a first language other than English were particularly likely to react neutrally (63%) (Figure 18; Figure 19; Figure 20). While English only-speakers were most likely to be excited when encountering a non-English song, they were also more likely to be annoyed (9.8%) than participants who spoke multiple languages (6.6%) (Figure 19; Figure 20). This could be because non-English songs may be out of the comfort zones for some people who only speak English. Of the participants who spoke multiple languages, none of the participants who spoke a first language other than English were annoyed when they encountered a non-English song (Figure 18).

The finding that English-only speakers are most likely to be excited when encountering a non-English song abides by Simon Frith’s theory regarding the appeal of music as cultural identity. People get excited by encountering something that seems exotic, because it represents an ideal of what they would like to be. Frith says that people can take pleasure from music that they don’t identify with by participating in an imagined form of democracy and desire (1996: 123). Frith’s claims about music and identity also further indicate that music can be used for cultural understanding:

“Music constructs our sense of identity through the direct experiences it offers of the body, time and sociability, experiences which enable us to place ourselves in imaginative cultural narratives. Such a fusion of imaginative fantasy and bodily practice marks also the integration of aesthetics and ethics.” (Frith, 1996: 124)

This may also explain why participants who can speak languages other than English are less excited and more neutral when they encounter non-English songs, as they find the material less exploratory - they may already be aware of the cultural narrative behind the music.
Conclusion

This paper addresses how streaming algorithms influence user discovery and acceptance of diverse music, with particular emphasis on whether recommendation algorithms create filter bubbles that limit exposure to diverse music. My survey results suggest that filter bubbles do exist in music streaming platforms, and those can affect exposure to diverse music--namely because music discovery in these platforms is drastically different than music discovery outside of them.

Several scholars argue that technology makes diverse music available to more people (Tepper and Hargittai, 2009 ; Leong and Wright, 2013). It is true that technology provides users with more opportunities to interact with diverse music than before the digital age. However, streaming services do not operate as boundless markets of music, because people search within limited, pre-made playlists for new songs. The amount of music available on the Internet could be compared to an infinite library, full of all editions, genres, authors, and books ever published. Even though this library is available to users, they do not have the time or desire to look through the entire library and search for new books. Instead, they turn to one section that contains some books they already like, and search within that aisle for books they are unfamiliar with. They do have an aspect of discovery, but it is out of a small sliver of the options that are globally available.

My survey results suggest that this phenomenon of limited discovery occurs on streaming services. A large majority of participants said that they searched for music actively and made
their own playlists while on streaming sites. Yet, over half of the participants used playlists recommended for them by the service, browsed playlists by topic, and rarely ever searched for new artists. These findings suggest the participants “actively searched for music” by either seeking artists and songs that they already knew or by looking through pre-made playlists that were recommended and/or curated by the streaming service. These observations indicate that music discovery on streaming websites operates differently than music discovery in the world at large, as users are discovering music within pre-constructed confines.

The types of encounters reported by the survey respondents also suggest a difference between a streaming environment and an environment of unlimited music. Over half of the participants rarely ever searched for new artists or non-English songs. Still, almost half of the participants were likely to spontaneously encounter one to two new artists, and a majority of participants were likely to listen to several different genres for every three hours they spent streaming. However, their likelihood for encountering a non-English song during this time was much lower. This occurrence suggests that while personalization algorithms indeed curate songs for users based on their perceived likes and background (people who did not actively seek out non-English songs were less likely to encounter them), there is also a level of opacity to these algorithms. Users are unaware of which aspects (such as preferred artists, genre, song language, personal demographics, etc.) are weighed highest by music platforms in terms of curating their music discovery.

While these results do indicate that the environment for streaming may not represent a world of unlimited options, they also suggest that users generally would respond positively rather than negatively if they were exposed more often to music from new artists or in different
languages. The popular reaction to spontaneously finding a new artist among participants was excitement, and the popular reaction to spontaneously finding a non-English song was neutrality. Users who only spoke English were the most likely group to be excited when encountering a non-English song, which suggests that spontaneous discovery and cultural learning could be welcomed by users of streaming sites.

**Limitations**

There are several limitations to this study. The primary limitation is that because this study was done in survey form, these answers were self-reported. Furthermore, a large majority of the participants were of the 18-25 age range, so these findings are largely predictive of millennial music media users. Additionally, there were more women who took this survey than men, and all of the respondents were fairly educated. This survey may have yielded more specific results if it had been done in small community with one native language. However, I chose to distribute this survey to English speakers who lived both inside and outside of the United States because I wanted at least half of my respondents to speak multiple languages.

**Implications for Future Research**

Due to the generally positive or neutral reactions of these participants when they encountered songs by new artists or foreign languages, it could be fascinating to further examine these interactions with diverse recommendations. If streaming sites recommended more diverse music, would users engage with these recommendations or avoid them? After a positive
experience with a new artist or non-English song, would these users be more likely seek diverse music in the future?

Another area for exploration involves user-curated playlists. While streaming services curate their top playlists, a host of playlists that people browse are curated by other users. These playlists could be more diverse, but they also could be recommended to users who have the same interests. An analysis could be performed to better understand how these playlists influence user discovery, social homophily, and identity formation on streaming services.

It would also be interesting to examine music streaming algorithms from the production side. A detailed analysis of streaming company policies could be fascinating in this regard. This analysis could interpret which criteria are applied to make user recommendations and how those factors influence the characteristics of songs recommended to users. A similar study could also illuminate the discriminatory potential of streaming recommendations by drawing conclusions on what types of music “should” be preferred by people of a certain demographic.

**Solutions**

Many scholars have posed different solutions for filter bubbles and discovery methods in the digital world (Ragno, Burges, and Herley, 2005; Baccigalupo and Plaza, 2006; Flexer, Schnitzer, Gasser, and Widmer, 2008; Levy and Bosteels, 2010; Hariri, Mobasher, and Burke, 2012). Reviglio offers that serendipity-driven recommender systems, as well as structural and informational nudging, could help expose users to more diverse information (2017). On the subject of news discovery, Tintarev suggests the use of a diversity aware recommendation model that considers both item and user diversity (2017). Tintarev offers that this would maximize the
amount of diverse content that users are exposed to without damaging any system reputation. Maria Taramigkou and her colleagues propose a system in which users can initiate their explorations of music genres by viewing the preferences of other users while taking a gradual path towards their desired genre (Taramigkou et al., 2013).

**Why Should We Care?**

The unlimited amount of music available online would suggest that there is more room for discovery now than ever. However, people find these boundless options overwhelming and turn to streaming sites, which offer personalization and recommendation algorithms. While streaming users still engage in discovery, they find new music by browsing playlists that are curated and/or recommended to them. Music consumption certainly lies on a balance between comfort and discovery, but streaming users operate in a pre-curated environment that is very much unlike a communal world of music. In discussing the effects of filter bubbles, Cynthia Dwork and Deirdre Mulligan note a common desire for digital media to operate like a traditional public forum, “where a measure of randomness and unpredictability yields a mix of discoveries and encounters that contribute to a more informed populace” (2013: 39). Unfortunately, recommendation algorithms do not yet (and may never) mimic the serendipity that one would experience on a street corner or sidewalk.

Dwork and Mulligan are among many scholars who have referenced the public sphere when making sense of how people should discover and interact with new information (Fraser, 1990). My observations indicate that streaming users are not interacting within a public sphere, but rather in an intensely curated environment that feeds their own preferences and biases.
Implications from this type of limited discovery can then be tied to cultural learning. The available literature lists music as a useful tool for identifying with one’s own culture, learning about other ways of life, and connecting with people of different backgrounds:

“But what makes music special - what makes it special for identity - is that it defines a space without boundaries (a game without frontiers). Music is thus the cultural form best able both to cross borders - sounds carry across fences and walls and oceans, across classes, races and nations - and to define places; in clubs, scenes, and raves, listening on headphones, radio and in the concert hall, we are only where the music takes us.” (Frith, 1996:125)

While music discovery has been an effective tool for empathy and communication across cultures, personalization and recommendation algorithms make it increasingly difficult for users to experience this type of discovery. As the popularity of streaming continues to rise and such algorithms continue to develop, each user’s “space without boundaries” will be confined by their own bubble. Time will tell if listeners are content with this bubble, if they burst through, or if they even notice its existence.
Section One: Additional Figures

These figures (10, 11, 12, 14, 15, 16, 18, 19, 20) are referenced in the “Results” chapter of this paper. They are separated by language groups. The figures display how often the respondent groups searched for and encountered non-English songs. They also display the reactions that each participant group had towards encountering non-English songs.

FIGURE 10:

FREQUENCY OF SEARCHING FOR NON-ENGLISH SONGS
[Participants with a first language other than English]

- HAVE NEVER SEARCHED FOR NON-ENGLISH SONGS
- RARELY EVER SEARCH FOR NON-ENGLISH SONGS
- 1-2 SONGS EVERY 3 HOURS
- 1-2 SONGS EVERY HOUR
- MORE THAN 2 SONGS EVERY HOUR

PERCENTAGE

36.3
45.5
18.2
FIGURE 14:

**FREQUENCY OF ENCOUNTERING NON-ENGLISH SONGS**  
[Participants with a first language other than English]

- Have Never Encountered a Non-English Song: 5
- Rarely Ever Encounter a Non-English Song: 20
- 1-2 Songs Every 3 Hours: 8.3
- 1-2 Songs Every Hour: 6.7
- More Than 2 Songs Every Hour: 9.1

FIGURE 15:

**FREQUENCY OF ENCOUNTERING NON-ENGLISH SONGS**  
[Participants Who Speak at Least Two Languages]

- Have Never Encountered a Non-English Song: 5
- Rarely Ever Encounter a Non-English Song: 58.3
- 1-2 Songs Every 3 Hours: 20
- 1-2 Songs Every Hour: 8.3
- More Than 2 Songs Every Hour: 6.7
FIGURE 16:

FREQUENCY OF ENCOUNTERING NON-ENGLISH SONGS
[English-Only Speakers]

HAVE NEVER ENCOUNTERED A NON-ENGLISH SONG: 24.4%
RARELY EVER ENCOUNTER A NON-ENGLISH SONG: 53.7%
1-2 SONGS EVERY 3 HOURS: 17%
1-2 SONGS EVERY HOUR: 2.4%
MORE THAN 2 SONGS EVERY HOUR: 2.4%

FIGURE 18:

REACTION TO ENCOUNTERING A NON-ENGLISH SONG
[Participants with a first language other than English]

Neutral Reaction: 63%
Excited: 27%
Amused: 9%
Annoyed: 0%
Angry: 0%
FIGURE 19:

**REACTION TO ENCOUNTERING A NON-ENGLISH SONG**

[Participants Who Speak at Least Two Languages]

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<tr>
<th>Reaction</th>
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<tbody>
<tr>
<td>Excited</td>
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<tr>
<td>Amused</td>
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</tr>
<tr>
<td>Neutral</td>
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<td>Annoyed</td>
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<tr>
<td>Angry</td>
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</table>

FIGURE 20:

**REACTION TO ENCOUNTERING NON-ENGLISH SONGS**

[English-Only Speakers]

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<tr>
<td>Angry</td>
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Section Two: Bibliography


