ARTIST GENDER REPRESENTATION IN MUSIC STREAMING

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ABSTRACT

This study examines gender representation in current music streaming, utilizing one of the world's largest streaming services. First, we found listeners generally stream fewer female or mixed-gender creator groups than male artists, with differences per genre. Second, while still relatively low, we found that recommendation-based streaming has a slightly higher proportion of female creators than "organic" listening (i.e., tracks that are not recommended by editors or algorithms). Third, we examined streaming data from 200,000 US users to determine the proportion of female artists in organic and recommended streams over a 28-day period and the relationship between recommended streams and users' future organic listening. The proportion of female artists in recommended streaming appears predictive of the proportion of female artists in organic streaming; these effects are moderated by gender and age. Fourth, this study also samples creators across different popularity levels, seeing more female and multi-gender groups at lower levels than in the middle tiers. However, (solo) female artists are better represented again in the superstars category, suggesting influence of selected superstars and genres. We conclude by discussing potential avenues in algorithmic auditing.

1. INTRODUCTION

Music has long presented barriers to success for underrepresented groups, including female artists [4, 22]. While gender inequities existed before the advent of streaming, the 7.4 billion dollar streaming industry [1] operates at a scale that merits critical examination. In particular, we examine whether music streaming presents similar imbalances or instead presents opportunities for greater gender parity. Music streaming services recommend tracks using a combination of human editorial and algorithmic decisions. Services learn users' musical taste and make predictions on tracks that may suit a given users' current activity, mood, or curiosity for new artists. Such recommendations may amplify or counter existing inequities. Research on music consumption suggests that online consumers of music tend to have more diverse listening than consumers who primarily discover their music through radio and TV [10] and personalized recommendations can introduce users to new and potentially more diverse content [17]. However, prior research has also indicated that personalized recommendations may funnel consumers into narrower content [7, 18]. Such conflicting results suggest that the impact of algorithmic recommendation may depend on specific data, models used, and the context in which they are applied. This study seeks to understand how one streaming service's recommendations reflect existing gender representation in the music industry as well as different approaches to making such assessments.

[1] http://wwwriaa.com/wp-content/uploads/2019/02/RIAA-2018-Year-End-Music-Industry-Revenue-Report.pdf

2. BACKGROUND & LITERATURE

2.1 Gender Representation in the Music Industry

Women have historically been underrepresented in the music industry relative to society as a whole. This is reflected in industry charts and awards. Smith et al, [22] found that 10.4% of Grammy nominees between 2013 and 2019 were female. In 2018's Hot 100 year-end Billboard Chart, 17.1% were female; a m:f ratio of 4.8 to one, lowest of the 7 years prior evaluated.

Women throughout history have been music role models and artists [11, 20], but barriers have limited their proportional representation in industry. Historically, women for example were not always allowed to be hired as musicians, or to play certain instruments at all [4]. Contemporary barriers reported by female artists include discounting of their abilities, lack of connections, unwanted stereotyping or sexualization, uncomfortable studio cultures, financial instability and lack of female role models [22].

Artists have to contend with expectations of genres and subcultures, including gendered trends and themes. In a content analysis of US music videos, Emerson [9] describes how black female artists appear to navigate both empowerment themes and aesthetic and social expectations. More specific genre (sub)cultures can play a role as well. In country music, Watson [24] found a decline between 1996 and 2016 in individual female artists played on country radio, and cites explicitly asserted beliefs by decision makers that playing more female artists would lead to less advertising revenue. In electronic dance music, Gavanas & Reitsamer [12] report female DJs navigating an environment where male entrepreneurs and DJs are much more visible and networked. In rock, the "groupie" description is a distinctly lower status label almost exclusively applied to women, even sometimes to those working in the industry, reinforcing a consumer rather than creative or production role [16].

Many music scenes however also explicitly provide space to explore non-conforming identities and roles [2, 13, 25]. Previous research has hypothesized that increased access to music afforded by the Internet disrupts barriers. For example, Epps & Dixon's [10] study on the consumption of hip hop music suggests that listeners who find the majority of their rap online consume more diverse tracks than listeners who consume most of their rap music on traditional media outlets. The same study also found that hip hop music on the Billboard charts (before streaming was included in these rankings) was less diverse on measures of lyrical themes, artist gender, and artist race than hip hop music shared online. While this work suggests that an increase in choice afforded by the internet is related to an increase in diversity of music consumption, few studies have been extended to evaluate the impact of music recommendation systems.

2.2 Bias in Algorithmic Recommendation Systems

A growing body of research examines biases in algorithmic systems. Often, these biases are extensions of biases that exist in broader society [6,23]. We might expect to see biases in algorithmic systems that mirror those in the music industry. However, impact also depends on objectives set, which can include a variety of metrics designed to broaden content consumption and diversity [15]. Choices within algorithmic models, which features to include, types of models used, also influence their output [5]. For gender and book recommendations, Ekstrand et al. [8], for example, found that when using skewed input, most collaborative filtering algorithms reflected user's profile tendencies, but that this effect was substantially stronger for implicit feedback recommendations (behavioral, e.g. clicks or reading) than explicit feedback (e.g. ratings).

In industry practice, a multitude of models build on top of each other. Algorithms designed to recommend music on streaming platforms utilize predetermined content and meta-data traits (e.g., tempo, genre, artist, historical period, etc.), as well as collaborative filtering techniques based on listening behavior by similar users. Some 'biases' are by design, such as when recommending only new releases on a new artists playlist, a playlist focused on women in rock only featuring women, or playlists focused on mood that may not include genres less suitable to that context. Other biases may be unintended, but can still be examined. For music, Aguiar et al. [1] examined gender imbalances on Spotify. They had insufficient evidence to conclude that female underrepresentation in streams was due to platform bias, they found pro-female bias in some playlists, and asserted a potential supply imbalance.

However, their work raises questions on the availability of baselines of streaming as a whole, the comparison at scale of programmed vs. non-programmed streams, and the influence of both streaming services and artist supply into these services. In this article, we build on their work by analyzing a larger data set of streams, providing insight into streaming behavior, as well as a hand-labeled sample of 'supply' in the hopes to provides the research community with baselines for further research.

We show that recommendation-based streaming has a slightly higher proportion of female artists than "organic", non-programmed listening. However, listeners generally stream fewer female or mixed-gender creator groups than male artists, making the proportion as a whole much lower than representation of women in society. We identify differences per genre that merit further investigation. Third, we find that indeed there is a relationship between recommended streams and users' future organic listening, moderated by gender and age. Fourth, we find that while supply of starting female artists plays a role, differing patterns of female representation at different popularity levels suggest differing investment patterns and again differences between genres. We conclude by discussing potential avenues in algorithmic auditing.

3. ORGANIC VS. PROGRAMMED STREAMS

Streams can be either programmed or non-programmed. Programmed streams originate from recommendations such as in algorithmic or editorial playlists, whereas non-programmed, 'organic' streams are explicitly asked-for through user-initiated actions such as search, or picking a playlist from a user's personal library.

Programmed streams include editorial playlists (curated by professional editors), and algorithmic playlists (those that are primarily created by machine learning models). Note that in practice, the latter distinction can be hard to make; editors manually selecting tracks for playlists still have algorithmic tools at their disposal. Similarly, algorithmic playlists are still human-designed with a specific purpose in mind (e.g. to discover new music), or may combine approaches using both editorial pools and algorithmic ranking, as discussed in Bonini & Gandini [3].

4. RESEARCH QUESTIONS

This study addresses the following questions through an analysis of data from a global music streaming service:

- RQ1: What is the current distribution of artist gender in music streaming, and how do recommended and user-initiated streams differ?
- RQ2: Does the proportion of female artist streams in recommended playlists predict the proportion of organic streams?
- RQ3: How do these results relate to gender distribution in creator 'supply' at different popularity levels?

For the first, we analyze a sample of a month of streams from a popular streaming service, and existing commercially available gender metadata. For the second, we take a sample of users, and investigate the relationship between their programmed and non-programmed (self-selected) streams, and the impact of listener characteristics. For the third, to counter the inherent popularity biases in our large-scale (meta)data, we take a random sample of creators at different levels of popularity, hand-label these creators and investigate the 'supply' proportion of female, male, non-binary and multi-gender artists and groups. Each of these will be discussed in their own section below.

5. REPRESENTATION IN STREAMING PATTERNS (RQ1)

We start this study by comparing programmed and non-programmed streams, and understanding the proportion of female-artist streams within this setting.

5.1 Methods

To obtain a baseline understanding of the artist-gender makeup of streaming, we present a sample containing 30 days of streams starting in early April 2020, from Spotify, a music streaming service with Millions of worldwide users [2] .

For purposes of this study, a *stream* is defined as a 30 second or longer play of a *track recording*. This time threshold minimizes the impact of skipped songs on our analysis. Note that some tracks may be streamed never, while others may get millions of streams. This means that popular artists and their streams will have a large impact on the analysis presented here, which is why we investigate representation at different levels of popularity in the section addressing RQ3.

For our analyses of streams, artist characteristics are supplied from commercially available metadata. Our focus here is on the main performing artist, not potential featured artists, songwriters, composers or producers. This data set has coverage on gender for around 86% of all streams sampled. For each artist entity in the data set, a gender entry states whether they are female, male, a mixed multi-gender creator group (e.g. a band, duo), or unknown/other. The latter covers both non-binary as well as unknown gender artists, meaning that we cannot distinguish between other gender identities in our at-scale analysis than male, female and multi-gender groups. This means this analysis is not inclusive to non-binary gender artists, even though binary conceptualization of gender is an inaccurate conceptualization [14, 21].

5.2 Results

In the 30 days analyzed, for all streams where gender information is available, around 1 in 5 have a female performing artist associated with them, see Fig 1. Of particular relevance to RQ1 was the comparison between programmed and organic streams. Female artists receive slightly more streams in programmed content than in organic streams (Pearson's $\chi^2 = 8e07, df = 2, p < 2.2e-16$, see Fig 1).

Streams with either a female artist or multi-gender group comprised respectively 21.75% of non-programmed (e.g. user search or library) streams, and 23.55% for programmed (recommended) streams.

[2] For recent numbers, see https://newsroom.spotify.com/company-info

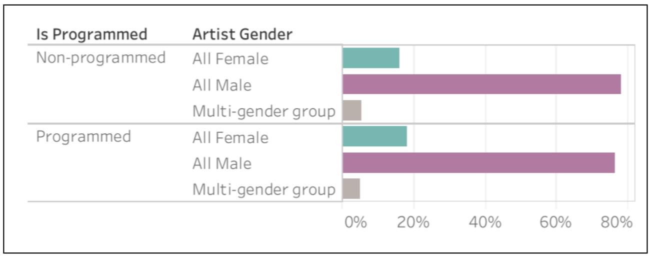

Figure 1. 'Programmed' vs. 'organic' streams, stream %. As discussed in section 5.1, non-binary gender not included due to data limitations.

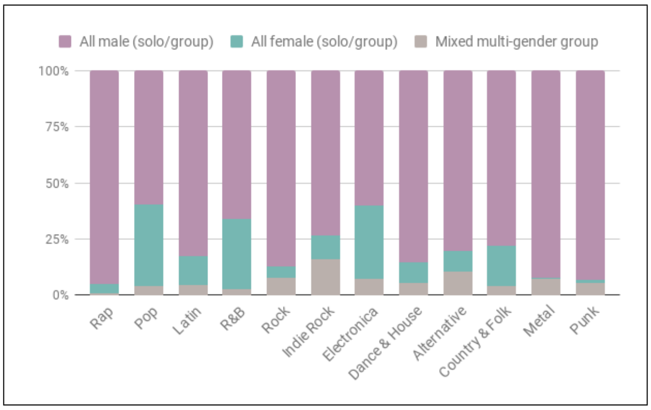

Figure 2. Proportions of streams for most popular genre groupings (cut-off for inclusion: 2% of streaming). Combined programmed and non-programmed streams.

We found considerable differences between genre streams (Fig 2), suggesting that subcultures can impact representation. For example, 95% of rap/hip hop streams were associated with male-only performing artists. For pop, around 40% of performers included a female artist or at least one female group member. For metal, all-female performer streams were rare (0.7%), with 7.0% mixed-gender groups.

This suggests the need for not only industry-wide, genre-agnostic follow up studies, but also genre-specific deep-dives that take into account sub-cultural processes, networks and industry structures.

6. PREDICTING ORGANIC CONSUMPTION (RQ2)

To better understand the relationship between programmed and non-programmed 'organic' listening, and the potential influence of recommendations, we then conducted an analysis centering user-level listening. This analysis uses a random US sample, and investigates whether the proportion of female artist streams in recommended playlists predict the proportion of organic streams listened to with various controls.

6.1 Methods

6.1.1 Sample

We limited our sample to US users who had a paid subscription and were between the self-reported ages of 13 and 90. We limited our sample to US users under the assertion that gender preferences in musical taste (whether explicit or implicit) are culturally dependent, and thus a cross-national analysis would present additional complexities beyond the scope of this project. Because of this, we decided to focus on US listeners because it was the largest population of users in our data set, and the market with which our research team was most familiar. One obvious alternative to this choice would be an international stratified sample; we hope future research will consider this approach. Gender was also self reported by users. From this larger population, we randomly sampled 200,000 active users for whom we had organic, editorial, and algorithmic streaming data in a 28-day period ending on September 30th, 2018. We chose a fall month to avoid seasonal and holiday-based differences in listening patterns, which are most pronounced at the end of the calendar year [19]. We allocated 60% of these data for training ($n = 120,000$), 20% for testing ($n = 40,000$), and 20% for validation ($n = 40,000$).

User characteristics, including gender and age, are gathered through the sampled streaming service's on-boarding process, during which new users set up their profile. Within our total sample ($N = 200,000$), 46% of listeners were female and 0.06% identified as non-binary. We also grouped participants into age categories.

For the purpose of this research, a user's *"top genre"* is defined as the highest-ranking genre when dividing their total streams by the number of streams in each genre. In total, there were 30 top genre categories. For 51% of listeners, pop was the most listened-to genre. Rock was the second, with a distant 15.6% of listeners.

6.1.2 Statistical Analysis

Our outcome variable of interest was the proportion of female artists in tracks streamed organically. In first assessing the data, we modeled the proportion of female artists in organically streamed tracks using ordinary least squares regression. We then introduced controls shown to be important in the larger literature. Finally, we included interaction terms between all main effects features and control features in the OLS regression. The final model equation is:

$$\hat{Y} = \beta_1 X + \beta_2 Z + \beta_3 X \cdot Z + \epsilon \qquad (1)$$

In this equation, $\hat{Y}$ is the predicted proportion of female artists streamed organically over a 28-day period, X represents the matrix of the main effects features plus the constant, Z represents the matrix of control variables, and ϵ is the error term.

In the end, we retained five dependent variables and the interactions between them, given that they were theoretically significant, had a reasonable amount of predictive power, and showed no collinearity with other variables. Table 1 summarizes the features selected for our final analysis without their interaction terms.

Thereafter, we applied several basis functions to see whether the model could be improved by including higher order polynomial features. The best fitting basis function was $\phi(X) = (x_1^1, x_1^2, ..., x_1^6, ...x_D^1, x_D^2, ..., x_D^6)$ (α = 0.01, R-Squared = .40). However, the small increase in R-squared statistic did not seem to justify increased model complexity and decreased interpretability. Five-fold cross validation was used to ensure the final model was not overfit to the data.

Variable	**Description**
Outcome Variable	
organic	Share of female artists streamed organically for longer than 30 seconds during a 28-day period
Main Effects Features	
algo	Share of female artists streamed via algorithmically programmed playlists for longer than 30 seconds during a 28-day period
editor	Share of female artists streamed via editor programmed playlists for longer than 30 seconds during a 28-day period
Control Features	
gender	Gender of user. One-hot encoded into female, male, and non-binary
age	Age of user. Self-reported age bucketed and one-hot encoded as categorical variables: 0-17, 18-24, 25-29, 30-34, 35-44, 45-54, and 55+
top genre	User's most listened to genre. One-hot encoded variable categorizes a user's most listened to genre. Such as afropop, atmospheric, blues, brazil, children, christian, classical, comedy, country, edm, hip hop, etc.

Table 1. Feature descriptions for RQ2

6.2 Results

For addressing RQ2, we used a randomly sampled dataset of US users and their streaming behavior. We iteratively built three models [3] to predict the effect of female artist

[3] Ideally, we would include all variables and their coefficients for the iterative models, considering space limitations we have limited the description to the final and best fitting model.

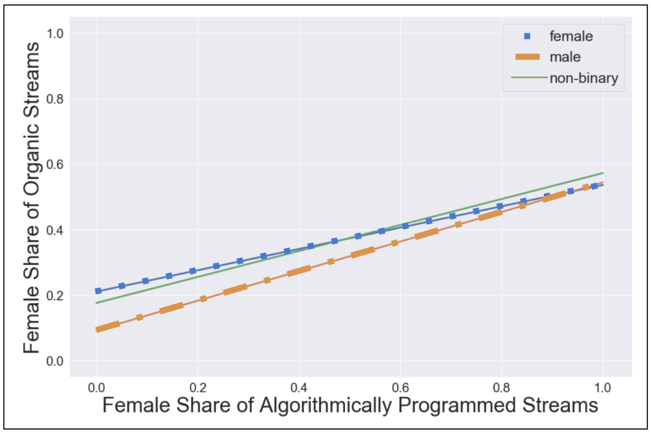

Figure 3. Plotting proportion of female artists in algorithmically recommended content on organic streaming of female artists when controlling for user age, gender, and top genre. Line style indicates moderation by listener gender.

share in algorithmic and editor programmed content on organic streaming of female artists. Additionally, we controlled for user age, gender, and top genre, and moderated by user age and gender. This final model's results are discussed below.

6.2.1 User Demographic Differences in Listening

Chi-squared tests revealed that there are no statistically significant differences between male and female users with regard to the share of female artists they stream (Pearson's $\chi^2 = 0.04, p = 0.98$). Additionally, Chi-squared tests revealed that there were no statistically significant differences between users of different age categories with regard to the female artist stream share (Pearson's $\chi^2 = 0.01, p = 1.0$). With this, we conclude that gender and age are independent of female artist stream share.

6.2.2 Linear Regression

In fitting our model, our null hypotheses were that the (1) there is no effect of programmed female artist share on organic female artist share and (2) effect of programmed female artist share on organic female artist share is not moderated by any of our demographic variables. With regard to listener gender, we found that the estimated effects for men were larger than corresponding effects for women ($\beta_{algoXmale} = .076, p < .001$). That is, compared to the women in our sample, men who streamed more female artists in algorithmically-programmed playlists were also more likely to listen to female artists organically. Figure 3 illustrates the moderated effects of algorithmic female share on organic female share by gender.

There are similar, yet weaker, associations for the interaction between gender and editor programmed content ($\beta_{editorXmale} = 0.014, p < .001$), as well as age and algorithmically programmed content. Notably, we found that the estimated effects for 18-24 year-olds ($\beta_{algoX18-24} = .026, p < .001$) and 25-29 year-olds ($\beta_{algoX25-29} = .047, p < .001$) were larger than corresponding effects for 45-54 ($\beta_{algoX45-54} = -.054, p < .001$) and 55+ year-olds ($\beta_{algoX45-54} = -.060, p < .001$). That is, compared to the 18-29 year-olds in our sample, those over the age of 45 who streamed more female artists in algorithmically-programmed playlists were less likely to listen to female artists organically. The interaction terms for age and algorithmically programmed content for 30-44 year-olds were not statistically significant.

Further, the strength of the model, as evaluated with the R-squared (r-squared = .374) and Root Mean Square Error (rmse =.152) statistics, was moderate. When evaluating this model's fit using the test set ($n = 40,000$), we found the r-squared statistic of the validation set was .361, meaning the model was not overfit to the training set and was the best performing model we built.

While main effects are often not interpretable in the presence of an interaction term, we can relax this guideline in this model because both features are captured by dichotomous variables where 0 is a meaningful value and within the range of the variable. For example, where a listener self-identifies as a woman, the interaction term is 0. In any cases when the interaction term is equal to 0, we can interpret the main effects. However, additional post-hoc tests were needed to conclude if the difference we have observed is, in fact, statistically significant, and can be inferred at the population level. When we conducted a GLH test of their joint population equality ($F(1, 59) = 1285, p < .001$), we found that we could reject this null hypothesis.

We conclude that we have sufficient evidence that there is a moderate, positive relationship between the proportion of female artists streamed on programmed playlists and the proportion of female artists listened to organically. Additionally, this relationship is moderated by both user gender identity and age in the population.

7. SUPPLY SIDE ANALYSIS (RQ3)

Large-scale analyses may offer insight in the proportion of streams that go to female artists or multi-gender groups being lower than male artists, but do not provide insight whether this reflects the 'supply' of female creators and multi-gender groups.

There is a long tail of less popular artists for whom data is scarce. Self-identification at this scale is not feasible for all artists who are streamed, not in the least for those deceased or without direct service access. This means that, for example, playlists focused on discovery of new artists, or those highlighting historic artists who are less well-known will have less complete, and potentially less accurate, associated metadata. To further investigate the presence, or supply, of female creators at different levels of popularity, we followed up with a manual sample across a wider range of creators.

7.1 Method

For our analyses of creator supply, we randomly sampled artists from six different levels of popularity. This, in an effort to reflect a spectrum of the artist community, from early projects to global superstars. Levels of popularity are defined as such: artists in the first level have 10 times more

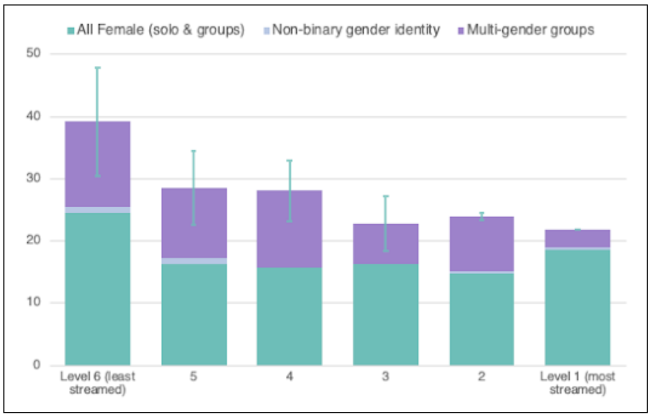

Figure 4. Percentage of Female, non-binary and multi-gender group 'supply' from least to most popular artists. Error bars: confidence levels of total (female + non-binary + multi-gender) % due to sample size vs. large (Millions) creator population at lower popularity levels

streams than the ones in the second level, who have 10 times more streams than the next, and so on. These were sampled in Feb 2020, and based on streams within the last 90 days. A professional team of data curators labeled 1330 creators in a similar manner to [22] (who manually sampled 800 chart entries). We here focused on a wider sample beyond charts, as well as including non-binary artists and multi-gender groups. It is noteworthy that information could not be found for at least 300 more creators, even by the expert data curation team.

7.2 Results

Representation of the aggregate of female + non-binary + multi-gender groups appears to differ at different levels of popularity (χ^2 = 12.865, df = 5, p-value = 0.02468). At entry-level, female representation is higher than at the middle levels, where it goes down slightly (see Figure 4). However, there is an uptick of female artists *better* in the superstars category, while less multi-gender groups are present. This suggests success of selected superstars, and influence of popular genres with higher female representation such as pop and R&B.

Even though more data collection would be necessary at lower popularity levels to get to results with higher confidence levels, we do now have a clear indication that both supply and demand matter. This suggests that the research community and services should address representation in streams overall, but that we as a community should especially also pay attention to how certain artists climb -or not- in popularity across platforms, and what factors lead to that climb.

8. DISCUSSION & CONCLUSION

In summary, this study resulted in several key findings. First, we found listeners generally stream fewer female or mixed creator groups than male artists. Second, we found that recommendation-based streaming has a slightly higher proportion of female creators than organic listening, but this proportion is still relatively low. Third, we found that gender and age of listener are independent of female artist stream share. Fourth, higher proportions of female artists in recommended streaming is predictive of higher proportions of female artists in organic streaming; these effects are moderated by gender and age. Younger age groups exhibited larger effect sizes, which may indicate that younger listeners are more open to taking (new) recommendations, or potentially more influenced by them. An alternative explanation may be that outside factors, such as terrestrial radio exposure, may be more salient for groups with smaller effect sizes. Future research should investigate the role of age, gender, and other identity markers in more depth. Finally, we find that in lower popularity levels, more multi-gender groups and more female creators appear to exist than in the middle - while at the top level (solo) female artists appear more present again. We have also highlighted the influence of hits on high-level stream numbers, as well as genre.

It is noteworthy that while examining gender representation is important, gender labeling in itself can be problematic. Performing labeling without self-identification can cause errors, and demographic data collection in itself presents significant risks. This results in a dilemma between inclusive representation vs. data minimization. In addition, some data ambiguity will always remain. People's expressed gender identities are not necessarily static; artists may come out as non-binary mid-career. Challenges also especially apply for historical as well as international art, and large collectives. Backing bands may or may not be taken into account in credits, orchestras and bands change and add or remove members. Information is scarce for lesser known artists, may be in other languages or terms than data curation or research teams may understand. Thus, striving for comparisons and repeated sampling rather than exact numbers and 'completeness' may be more productive tasks.

In this study, we primarily looked at streaming outcomes in aggregate, rather than who is 'shown' as a recommendation in a specific product context. Results may be skewed by top-level streaming outcomes, and higher popularity genres such as pop which have higher female representation than other genres. Although the results in this study are not causal, they do suggest that further work on the ability of content recommendations to diversify user listening habits are warranted. We primarily discussed descriptive baselines; future studies should explore alternative models and sampling approaches, potentially consider causal inference methods that do not require experimentation, or experimental designs that thoughtfully contend with the ethical concerns of manipulating user experiences on a commercial platform. Future work should also study how gender intersects with genre and subculture, as well as other factors such as race/ethnicity, locale and congruence with existing cultural expectations.

We conclude that there are barriers to entry, and to climbing to the top, but that streaming services may be able to challenge structural inequities by spotlighting underrepresented artists in their recommendations.

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