Free Lunch? Spotify and the Cost of “Freemium” Music

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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Introduction

Spotify is a popular streaming application for music, podcasts, and audiobooks (Spotify AB, 2022). The service runs on a ‘freemium’ business model, granting access to its content library in exchange for listening to advertisements or paying a monthly premium. In either version, users can listen from Spotify’s collections or create their own playlists, although Premium grants access to more of the app’s features. Unlike iTunes, where songs are purchased and downloaded, listeners can only access Spotify’s music through its platform due to its licensing (Spotify AB, 2022). This distinction between ownership and access is precisely how the service attracts new users: why pay $15 for ten songs when Spotify offers “millions” (Spotify AB, 2022)?

Because of this, Spotify has become a breakout success in the tech and music industries. The IMS Business Report 2023 estimates that Spotify possesses 30.5% of global music streaming application subscribers, or over 200 million users— a portion greater than Apple, Youtube, or Tencent (Kale, 2023). Spotify has become so ubiquitous that Rasmus Fleischer has described "Spotification” in other media industries as their startups have tried and failed to copy the service’s success (2021). Despite posting an annual revenue of 11.72 billion euros (12.74 billion USD) in 2022, Spotify has never reported a profit (Iqbal, 2024). So, how can such a company survive without turning a profit? How did Spotify grow in such conditions? What effect did this have on listener experience?

In this paper, I argue that Spotify’s pursuit of continued investment and expanding markets has come at the cost of user experience. From the beginning, the company’s reliance on venture capital meant it had to constantly build hype around its continued growth instead of creating a profitable business model. Thus, Spotify’s developers rapidly adapted to changing circumstances and competing platforms. The technologies and business alliances Spotify adopted have hurt user experience due to a lack of transparency surrounding the use of user data, the suppression of diversity in the algorithmic recommendations, and reinforced presentations of gender and race in the user interface.

In the next sections, I review my methodology and frameworks before providing historical context for Spotify's development and an analysis of how each component of Spotify impacts listener experience. This includes an examination of the service's data aggregation and usage practices, algorithmic recommendation system, and its user interface. Finally, I show how such technological choices reinforce the service's control over listener experience to placate their allies in the music industries and continue growth.

Methodology and Frameworks

I analyze literature from the UVA library and online sources to show how Spotify's technological features and business alliances have impacted our relationship with music. Experts from various disciplines have separately analyzed Spotify's features, including STS researchers like in Maria Eriksson and collaborators' *Spotify Teardown* (2019), computational research such as that by Dominik Kowald and collaborators (2020), interface design research such as Ann Werner (2020), and marketing research about the service's impact on other industries like Rasmus Fleischer (2021). Examining the differences between research conducted within Spotify and independent studies reveals disparities in Spotify's self-presentation and its actual impact on listener experience across academic fields.

Actor-network theory (ANT) can explain how certain financial decisions affect the technical components of Spotify's streaming services and vice versa. ANT frames social and technological phenomena as “actors” which work together in “networks” to achieve common goals, or points of obligatory passage. Similar to how Michel Callon identified St. Brieuc Bay researchers unifying the scallops, fishermen, and other scientists for conservation efforts (1984, 19), Spotify’s founders identified its “place at the intersection of different industries: music and technology, advertising and finance” (Eriksson et al., 46). The framework describes how Spotify can link artists, mathematical models, data centers, record labels, network, listeners, and advertiser with a single tap by modeling them as sociotechnical actors connected by a point of obligatory passage.

Since Spotify relies on algorithmically generated content, I also examine the app’s use of mathematical models through Cathy O’Neil’s *Weapons of Math Destruction* framework. O’Neil points to three qualities for judging the harm of mathematical models: 1) opacity, or to what extent users understand how the model works, 2) damage, or the physical, mental, social, or financial cost inflicted onto users as a result of the model, and 3) scale, or the total number of users affected by the model. With Spotify’s over 200 million subscribers, the case for ‘scale’ is quite evident, but assessing the platform’s opacity and damage requires further examination of its data practices and interface design.

Investigating the app’s interface requires frameworks on race, gender, and nationality, as Werner notes that “ the use of genre and previous choices…in Spotify’s construction of similarity…reinforce connections between artists similar in terms of gender and race” (2020, 87). Robin James’ “neoliberal sophrosyne” serves as a good framework for examining the reinforcement of normalized notions of gender and race on Spotify’s platform, as the app’s algorithms literally “translate normalized statistical distributions into structures of subjectivity and criteria for moral and political personhood” (2019, 130). Analyzing how these ideal constructions of music listeners and creators interact with the app's presentations of race, gender, and nationality requires further investigation of its interface.

A Brief History of Spotify

Daniel Ek and Martin Lorentzon launched Spotify as a startup on April 23, 2006, in Stockholm, Sweden (Iqbal, 2024). The two men, multimillionaires with a background in advertising, created Spotify as an legal alternative to illegal file-sharing websites prevalent in Sweden (Eriksson et al., 40-41). Ek and Lorentzon built the app's initial beta with the same peer-to-peer networks that file-sharing websites like Napster used, with many files originating from the Pirate Bay (Eriksson et al., 2019, 45). Spotify did not publicly launch until it secured licensing agreements with Swedish music publishers, with the company having to "remove unlicensed music from its service" (Eriksson et al., 2019, 45). With the advent of the 2009 Pirate Bay cases, Spotify represented the "win for consumers that still [meant] billions in industry profits" (Alderman, 2001, 186).

In practice, the startup faced many obstacles before becoming the dominant music streaming service it is today. To continue earning funds, the service had to build excitement around its continued growth, lest it fail to attract investment and go out of business. Seeking other sources of revenue besides selling advertisements, Spotify created a premium subscription version in 2008, which came with phone plans and other services (Eriksson et al., 2019, 51). Spotify also shifted to a "platform" model in 2011, allowing users to connect their Facebook profiles and "friend" other users (Eriksson et al., 2019, 52). Finally, Spotify added an algorithmically generated "Related Artists" function, now known as "Fans Also Like" (Eriksson et al., 2019, 53). The app's continued growth convinced Warner Music, the last of the major U.S. music labels, to agree to a U.S. launch of Spotify in July 2011.

From there, Spotify continued developing more features to raise the company's value ahead of an initial public offering (IPO). While some, like frictionless music sharing, saw limited success, the app soon shifted from its on-demand model of music distribution to more personalized recommendations due to competition from Pandora, Songza, and Apple Music (Eriksson et al, 2019, 59). Spotify acquired music technology companies like Tunigo in May 2013 and Echo Next in 2014 to bolster development of algorithmic recommendation systems (Etherington, 2013 and Lunden, 2014). The service also "[shut down one] of the internet's largest P2P networks, which was then replaced by central servers…" (Eriksson et al., 2019, 63), giving Spotify more control over its music distribution and data aggregation. Spotify's library expanded to include podcasts and audiobooks, leading up to its 2018 initial public offering (IPO), where Spotify's value was estimated at $29.5 billion (Deahl, 2018).

While most of the service's users reside in Europe and North America, the service has made efforts to continue expanding internationally since its IPO (Richter, 2021). Most of its users are 18-34, and its gender demographic is roughly equal with slightly more women (Iqbal, 2024). With new algorithmically curated playlists like "Your Daily Drive," "What's New," and "Daylist," the service continues to cultivate its image as a "producer" of new listening experiences, including several exclusive podcasts, such as the *The Joe Rogan Experience*.

Data Aggregation, Infrastructure, and Usage

Spotify depends on three flows of data: 1) audio from creators to listeners, 2) advertisements from brands to listeners, and 3) behavioral data from listeners to algorithms.

While data flow depends on existing hardware, software, and network infrastructure to ensure reliable and secure travel, I focus on the overall collection, storage, and use of Spotify's data as well as the flow of money accompanying each mechanism. The service's choice to complicate and hide its aggregation of data for per-usage royalties and programmatic advertising gears the service to appease two major allies: record labels and venture capitalists.

For the licensing and distribution of audio, Spotify partners with third-parties like DistroKid, CD Baby, or Record Union, with sixty-three such distributors listed on its providers page (Spotify AB, n.d.-a). While each distributor sets its own pricing, Eriksson and collaborators report that this reliance on third-parties "gets longer for smaller repertoire owners, as compared to major rights holders" (2019, 95). With each stream worth less than a cent, independent creators pay for distribution at a loss if their music is not popular enough, whereas major rights holders with mainstream artists can more easily turn a profit (Iqbal, 2024). This decision makes sense in context— Spotify would not have expanded to the United States without the approval of record companies like Universal, Sony, and Warner, that benefit most from this distribution model (Eriksson et al., 2019, 32).

Spotify's data storage also reflects this shift from decentralized to centralized control. The service originally achieved the low latency required for continuous listening through the use of peer-to-peer (P2P) networks, which bolstered the speed of loading each track by divvying the workload between "peer" devices that already had the track (Eriksson et al., 2019, 89-90). The service moved away from P2P to its own data centers and then the Google Cloud Platform (Google Cloud, n.d.). While benefits of this partnership included cheaper and more reliable data storage, Google Cloud also gives Spotify access to AI tools for improving Spotify's algorithmic recommendations (Google Cloud, 2023). Thus, the service distributes audio not only to listeners but also machine learning models to taxonomize and recommend its content.

Spotify's advertisements are similarly aggregated, stored, and analyzed through third-party services. The app partners with Supply-Side Platforms (SSP) to determine what brands to target, what type of ads to support, and how to price those ads (Eriksson et al., 2019, 169). The SSP then posts "impressions" featuring this information on ad exchanges and Demand-Side Platforms (DSP), where brands looking to advertise might buy packages that include Spotify's inventory, bid on such Spotify's impressions, or contact Spotify directly for more specific campaigns (Eriksson et al., 2019, 169). Instead of being used to maintain the enrollment of major record labels, the service employs many intermediaries to maximize ad revenue and impress investors. Spotify bypasses traditional routes for ad buying through its "super-intermediation" of media buying, allowing Spotify to retain more revenue and charge more for its user-targeted advertising campaigns (Eriksson et al., 2019, 170).

Herein lies the key to Spotify's success: user data. As part of the European Union, the service must report the purpose, legal justification, and categories of personal data it collects (Spotify AB, n.d.-b). These categories include streaming history, playlist content, library content, search history, payment information, voice input, and user-specific data, including date of birth, gender, country, postal address, and mobile number (Spotify AB, n.d.-c), all of which totals "over 100 billion data points per day based on the activities of its 207 million active users" (Cooper, 2019). Access to everyone's playlists and streaming history gives the platform insight into each user's mental state, allowing Spotify to profile users based on their demographic data and music tastes (Eriksson, 2019, 137). The service uses such insight to improve its algorithmic recommendations and its advertising market, where "consumer data that are extracted by various data suppliers and aggregated by one or several data management platforms (e.g., BlueKai)" is exchanged (Eriksson et al., 2019, 170). Spotify hides the exchange of user data on its platform, with its advertising buying markets and prices fully private (Eriksson et al., 2019, 166), which prevents users from knowing the value of their data. Those who wish to opt out of programmatic advertising have only one option: to pay for Spotify Premium, which is coincidentally the most advertised service on Spotify Free (Eriksson et al., 2019, 168). Thus, regardless of what the user chooses, Spotify can pay royalties to major labels, generate revenue via subscriptions or ads, and collect data to continue improving its recommendations.

Algorithmic Recommendation Systems and Consumption Diversity

All these data prompts the question: what even are these models that Spotify uses to generate recommendations? For Spotify to manage the sheer amount of content it recommends daily, it needs some systematic method to 1) analyze the most relevant traits of each category of data and 2) draw connections between these traits. Modeling is the transformation of data into such traits, and algorithms describe the steps that Spotify takes to model data and generate recommendations.

For example, if I listen to video game music and the system knows that I am a male twenty-two-year-old, then a reasonable prediction might be that I would listen to more video game music or click on a video game advertisement. Of course, it could be that I mistakenly clicked on the track or only like listening to one specific track, but the algorithm can only make predictions based on its data and objectives. This may lead the algorithm to act contrary to its developers' intent, like if I end up buying the game advertised and stop listening to music on Spotify. Algorithms therefore constitute their own actor-network that may require intervention from other actors, like data and developers. Spotify has enrolled several algorithms to not only generate revenue but also maintain relationships with its partners, whose motivations may sometimes be at odds with the algorithms.

Spotify's algorithm, Bandits for Recommendations as Treatments (BaRT), uses natural language processing and audio analysis to generate song features and filter them into recommendations (Berner, 2022). Its name comes from the "multi-armed bandit problem," where a gambler determines what levers or "arms" of a many-armed slot machine or "bandit" to pull to maximize their winnings (Thingstad, 2023, 14). BaRT chooses what songs to put in a user's playlists, search results, and play queues to maximize the total time they spend on the service, often choosing between songs listeners liked previously and songs they haven't heard before (Thingstad, 2023, 13). BaRT's 'collaborative filtering,' where it examines how similar users reacted to prior recommendations, therefore balances such choices to expose users to as much Spotify content as possible.

One metric for BaRT's performance is consumption diversity, or how varied a user's music library is over time. If the algorithm can optimize listener exposure to Spotify's library of over 100 million songs, then it should introduce them to new songs and diversify their taste profile over time (Iqbal, 2024). Researchers at Spotify report that algorithmically driven listening results in less consumption diversity compared to organic consumption (Anderson et al., 2020, 2155). While "users [may] use recommendations to satisfy their similarity-based needs and organic streaming to satisfy their exploration-based needs," such an explanation does not deny that users whose tastes became more diverse did so by decreasing their algorithmic listening (Anderson et al., 2020, 2159). Adrian Leisewitz and George Musgrave corroborate these results, finding that "after employing the playlist for one week [for] new music discovery, there was no attachment demonstrated amongst consumers with a low willingness to form attachment, and only limited to moderate attachment amongst consumers with a high willingness to form attachment" (2022, 90). BaRT's poor consumption diversity suggests that it may fulfill another goal relevant for Spotify to increase investment or maintain its partnerships.

Spotify's radio function also supports this claim. In an experiment measuring how often BaRT would repeat tracks in Spotify's "Radio" function, researchers found that "if a radio loop started with 'Dancing Queen,' it was played again by the Spotify Radio algorithms after about fifty tracks," with other radios repeating songs every seventy tracks (Eriksson et al., 2019, 101). This pattern points to a "filter bubble" effect, where users are mostly recommended songs similar to music they already like (Thingstad, 2023, 25). BaRT prioritizes short-term listener satisfaction to the detriment of their long-term experience, shutting out smaller artists whose work is never recommended.

BaRT's poor performance recommending niche music over more popular music further compounds this problem. In another experiment measuring the impact of AI ranking systems, Ashton Anderson and collaborators found that "recommendation models perform much better for specialists than for generalists" (2020, 2164), indicating that users whose music preferences are more spread out receive worse recommendations than those who listen to more specific music. While Kowald and collaborators showed this bias was also present in the same system behind Last.fm, a Spotify competitor (2020, 35), Eriksson and collaborators found BaRT actually could recommend more diverse music , finding that some bot accounts with differing ages "received a much larger and more varied set of recommendations" (Eriksson et al., 2018, 134). To what extent Spotify can address this discrepancy is not known; however, that "approximately 20 percent of Spotify's catalog has not been listened to…once" indicates that BaRT alone cannot address this shortfall (Eriksson et al., 2018, 98).

This discrepancy in recommendation frequency between more and less popular music furthers Spotify's goal of maintaining its licensing agreements with major record labels. If BaRT proactively recommends niche artists, then Spotify would pay more artists who have not signed with the same record labels that enabled Spotify's entry to market. Even though the service could modify BaRT to improve user experience, it makes no sense to potentially alienate its partners. The service also has an incentive to control what model information gets released, as competitors could use such details to develop better song and ad recommendations. So, current research cannot detail BaRT's mechanisms, and, like data, any activity from the model gets presented as magic in the app's interface.

Interface Design and Intersecting Frameworks

Spotify's users never interact directly with the app's data or algorithms, since its interface wraps all interactions into search results, playlist suggestions, similar artists, and algorithmically generated mixes. These playlists include "Discover Weekly," a compilation of recommended tracks that the user has never listened to, and various genre-based and mood-based mixes, such as "golden hour" or "sad boy anthems." Recent additions include "Daylist," a playlist which shifts between genres or moods that the user experiences at that time or day of the week, like "indie chill actor Sunday night." By presenting itself as in tune with listeners' emotions, the application "promise[s] to…[foster] happiness— even in times of utter darkness" (Eriksson et al., 2019, 125). If Spotify can know and therefore influence our emotions based on our current listening behavior, how else could it influence our perception of the world? By employing additional frameworks to examine its interface, my review has found that Spotify's presentation of genre reinforces perceptions of listeners and creators in terms of gender, race, and nationality to align with the music industry and expand into other markets.

Even though women make up 56% of its listeners, Spotify rarely recommends its female artists as often as its male artists, "othering" them in a way worse than in prior distribution mediums. Luis Aguiar and collaborators found that the percentage of songs created by women was 21.5% in 2017, which contributed to female artists' low share of streaming (3). While Spotify is not solely to blame, Eriksson and collaborators found that "the service reproduces an often-criticized notion of music production as a domain of masculinity [such that] music consumption… is portrayed as a female undertaking" (2019, 127). Werner's research examining Spotify's "Related Artists" function also found that few female, black, or brown artists were found within three steps of Damien Rice, a white Irish rock artist (Werner, 2020, 84). This ultimately causes the few female artists promoted to be singled out, with Werner noting "In a record store Beyoncé or Ciara might be placed next to a male artist within mainstream R&B… but Spotify Related Artists lists them next to young African American top-selling females" (Werner, 2020, 87). The platform amplifies differences in artists' gender by segregating them into different recommendations.

Spotify similarly separates recommendations based on nationality and race by collecting the IP addresses of its users (Spotify AB, n.d.-c). Each IP address reveals the country each user resides in, allowing Spotify to base recommendations on user nationality like Eriksson and collaborators' findings that "Latin music…was typically found toward the bottom of the page—except for users registered in Spain and Mexico, to whom it was suggested among the top choices" (2019, 121). This in itself is not bad— expecting everyone to enjoy foreign-language music is unreasonable— but Spotify's use of genre to embody this separation leads to further marginalization of niche artists. As Tom Johnson notes about Spotify's musical categorization, American conceptions of genre are deeply entwined with historical racial disparities in musical expression, such that "folk taxonomies of largely white and generally economically privileged audiences drive the capitalist perspectives of musical categorization most expedient for industry profit" (Johnson, 2020, 177-178). Such ideas of genre not only restrict what gets played but also what gets created, with racialized ideas of genre limiting the recognition of artists like Frank Ocean, Moses Sumney, India.Arie, and Tyler the Creator both in the industry and on Spotify (Johnson, 2020, 192). In this, the platform has failed to acknowledge many of its greatest artists and instead has reinforced the disparities implicit to their definitions of genre.

Spotify's marketing team adopted such an interface to "reinforce the notion of the user as a happy, entrepreneurial subject— young, urban, middle-class" (Eriksson et al., 2018). This does not mean that the app ignores difficult topics involving race, gender, or nationality, but rather it only presents them to the degree that their target audience is comfortable with. If the listener prefers the Beatles, why not just recommend more of John Lennon or the Beach Boys? If they enjoy Alicia Keys, why not just recommend more from Destiny's Child or Ciara? The result of Spotify's ambivalence is ultimately a reinforcement of BaRT's 'filter bubble' in its conceptions of genre to the benefit of its business partners. If Spotify presented more music outside the confines of genre, that would promote more niche music and alienate others in the industry, which would be unacceptable for seeking future investments and markets.

Discussion

The Spotify actor network has one goal: to bolster growth, as the service's success depends on building up hype to secure funding from venture capitalists and licensing from major record labels (Eriksson et al., 2019, 33-34). The service regularly enrolls and de-enrolls technologies, companies, and markets as a result, from its shift to Google Cloud storage, partnership with Facebook, and its expansion into podcasts and audiobooks. These changes have not always improved overall listening experience—the dismantling of P2P networks caused no visible shift in the app's ability to provide music and Spotify even had to roll back its frictionless sharing feature after complaints regarding privacy (Eriksson et al., 2019, 56). Other technologies, like BaRT's decrease in music diversity and the interface's sidelining of artists based on gender and race, even contribute to a worse user listening experience.

From an actor-network standpoint, Spotify's obligatory passage point is not that the user has the best listening experience, but rather that they continue sharing their data for training better models. Better visualizing musical attributes and increasing user control over such features via sliders or buttons significantly increases exposure to new music (Millecamp et al., 2018, 108). Such interface elements would bolster overall music diversity and long-term listener engagement. Spotify already spends 1.39 billion euros (1.51 billion USD) a year on research and development (Götting, 2023), but has not incorporated such elements since it would benefit more musicians not tied to the major record labels in its actor-network. Likewise, revealing information about the use of listener data would increase user awareness of the data's value, driving them away from the service. Spotify prioritizes control over how users interact with its technology over potential profits generated by giving users more freedom with their preferences.

We can easily see how frameworks like Robin James' biopolitics apply: by making the service serve mainstream interests better than niche artists, Spotify maintains its alliances with major record labels and tailors its technologies to follow suit, enforcing neoliberal sophrosyne onto its users. James describes 'sophrosyne' of the presentation of gender as "exhibiting the proper distribution of signal and noise" such that "feminine-presenting phenomena can 'lean in' to patriarchal privilege and avoid the negative effects of structural feminization" (2019, 146). Less mainstream music on Spotify is thus "immoderately noisy or loud because they distort rather than amplify patriarchy" or in this case, music tied to major record labels, so such music is "structurally feminized and perceptually coded into the red…" (James, 2019, 146). Spotify codes such music "into the red" by limiting recommendations of less popular music and marginalizing artists from less represented groups through its use of genre.

Such music often goes unstreamed and unplayed, and popular content, including that like *The Joe Rogan Experience's* promotion of misinformation about COVID-19, is put into the forefront. Spotify meets O'Neil's criteria for damage, as its algorithm harms users by decreasing consumption diversity and marginalizes creators through its presentation of genre. Since the platform is opaque in its use of data, is harmful in its marginalization of niche artists, and acts at a global scale, Spotify qualifies as a "weapon of math destruction."

Conclusion

As the first music streaming platform of its kind, Spotify is widely hailed as the savior of the digital music industry, battling illegal file-sharing by compensating artists while providing endless music streaming in over 170 markets (Iqbal, 2024). While Spotify has fulfilled Napster's goal of jump-starting the music-streaming industry, this narrative paints a rosy picture of the platform. To achieve this unprecedented growth, Spotify built and rebuilt its infrastructure to win over major record labels and venture capitalists. This includes restructuring its data aggregation infrastructure to hide the distribution of music, ad, and user data, training a recommendation engine that performs better for more mainstream music, and developing an interface that reinforces such priorities through influencing emotional state while marginalizing other perspectives on the platform. Thus, as Eriksson and collaborators note, “Spotify is a mediator, rather than an intermediary, that actively reproduces the meaning of the songs” via “ a music classification and recommender system whose output is data for advertising” (2018, 171). As a result, the platform acts as a “weapon of math destruction” by refusing changes that would improve listener experience, instead enforcing an order that benefits its allies at the expense of individual users and artists.

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