THE SOUNDTRACK OF DISCOVERY: EXPLORING THE IMPACT OF SPOTIFY’S RECOMMENDER SYSTEM AND ALGORITHM AWARENESS ON MUSIC TASTE EXPANSION

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ABSTRACT (150 max, 100 min.)

Music streaming platforms such as Spotify have transformed the landscape of music consumption through sophisticated recommender systems, which markedly shape user preferences and behaviors (Hodgson, 2021; Seaver, 2022). Utilizing multiple regression analysis, our study investigates the influence of “algorithm awareness” (AA) and “satisfaction with the recommender system” (SRS) on the expansion of music taste (EMT) among Spotify’s primary demographic, individuals aged 25–34 (n=129). This age group constitutes the most substantial user base of Spotify, providing essential insights into the effects of algorithmic engagement (Iqbal, 2023). Our results indicate that while SRS significantly enhances EMT, AA does not have a notable impact. These findings contribute to the broader dialogue on human-artificial intelligence interactions and the role of algorithms in everyday life, underscoring the significance of algorithm literacy and its influence on user behavior (Dogruel et al., 2021).

Keywords:
Algorithm Literacy, Algorithm Awareness, Recommender System, Music Streaming Service, Spotify

Music thrives at the intersection of culture, technology, and commerce. It's the single most influential global art form, with an unmatched ability to attract audiences, drive social interaction, transcend borders, and unite people" (IFPI, 2023, p. 3). This perspective, articulated by Robert Kyncl, CEO of Warner Music Group, underscores music's integral role in cultural formation and influence worldwide. The advent of Web 2.0 has catalyzed significant technological advancements, reshaping people's engagement with music profoundly. Traditional methods of music consumption have been supplanted by the ubiquity of music streaming services such as Spotify, Apple Music, Amazon Music, YouTube Music, Tidal, and Deezer, which now represent the predominant mode of experiencing recorded music (Hodgson, 2021; Seaver, 2022).

Spotify, originating from Sweden, has been at the forefront of this transformation. Since its inception in 2008, this erstwhile startup has been pivotal in redefining the music industry. Through its sophisticated recommender systems, Spotify offers personalized and curated musical experiences, simplifying the exploration of its vast library, which is now accessible in over 180 markets, encompassing over 100 million tracks and 6 million podcasts (Spotify, 2024). With 615 million users, including 239 million paid subscribers, the streaming giant currently holds a significant global market share of 31.7%. Spotify not only dominates the market but also serves as a primary revenue generator within the recorded music industry (Music Industry Blog, 2024).

Music streaming services mark a significant departure from traditional methods of music consumption, such as purchasing physical albums or downloading individual tracks. These platforms enable users to access extensive song libraries instantaneously across multiple devices. With a click, subscribers can explore new artists, immerse themselves in diverse musical genres, assemble personal playlists of favored tracks, or experience tailor-made playlists that reflect their listening preferences (Hesmondhalgh, 2021).

At the heart of this personalized experience are the recommender systems, which utilize sophisticated algorithms to analyze a plethora of user data, which, in the case of music streaming services, include listening behavior, playlist selection, and user-generated content. This analysis enables the creation of tailored music recommendations for each subscriber (Prey, 2019). Acting as intricate information filters, recommender systems assist users in navigating the platforms' expansive music libraries. They continuously suggest new findings and update selections, actively shaping user consumption patterns (Hu et al., 2014; Jacobson et al., 2016).

The effects of such recommender systems on user behavior have already been studied in various domains, including e-commerce, movie recommendations, and social media platforms (Aivazoglou et al., 2019; Subramaniyaswamy et al., 2017; Zanker et al., 2010). These systems not only mold user preferences and decision-making but also enhance customer satisfaction. In music streaming, the role of these systems is particularly critical, as they can dramatically influence user engagement by introducing listeners to new artists, genres, and tracks that resonate with their tastes.

Empirical studies further underscore this impact. Datta et al. (2017) found that using the music streaming platform Spotify led to increased plays, diversity, and new music discovery. This could lead to a more diverse music market, from which especially independent musicians and smaller record companies might benefit. Another study by Way et al. (2020) found that adopting Spotify increased listeners' preference to stream local content and created a so-called home bias consistent through different genres and age groups. Bello and Garcia (2021) investigated music chart composition on iTunes and Spotify, finding a consistent increase in the diversity of songs, artists, and music labels at the top of the charts on both platforms from 2014 to 2020 and 2017 to 2020, respectively. However, genre diversity exhibited a contrasting trend, with increasing homogeneity in styles represented on the charts during this period.

Substantial research has been undertaken to assess how recommender systems in music streaming services influence user engagement and listening behaviors. For instance, Anderson et al. (2020) demonstrated that Spotify users exhibited increased diversity in their music consumption, which was even more pronounced when they engaged in organic listening behaviors rather than relying on algorithmic recommendations. This suggests a nuanced interaction between user choice and algorithmic influence. Furthermore, Holtz et al. (2020) discovered that while personalized recommender systems intensified listening activities on Spotify, they also nudged users towards a more homogeneous music selection, deviating from the listening patterns of similar users over time.

This study seeks to investigate the impact of recommender systems on music discovery and taste expansion within music streaming services, with a particular emphasis on Spotify, the predominant market leader. Unlike existing research focusing on the general changes in music consumption brought by music streaming platforms, our study will also consider the role of algorithm awareness. Here, we explore how users' understanding that Spotify's recommendations are algorithmically generated impacts their listening preferences. This is of great importance because existing literature on the concept of algorithm awareness in general, its optimal measurement, and its effects on consumption behavior remains scarce. This research gap exists not only in music streaming but across various industries that employ recommender systems and, thereby, algorithms.

Our research will examine the preferences and experiences of individuals aged 25-34, representing Spotify's most engaged audience segment. By analyzing how these users interact with Spotify's recommender systems, the study aims to uncover how digital platforms are not merely passive repositories of content but active participants in shaping cultural landscapes. Our central research question is: "To what extent do satisfaction with Spotify's recommender system and algorithm awareness predict the expansion of music taste among 25-34-year-olds?".

Theoretical Framework

Spotify's Recommender System. (SRS)

Music streaming services like Spotify have significantly transformed how users interact with music, mainly through their sophisticated recommender systems. These systems, proprietary in nature and not extensively detailed in academic literature, harness vast amounts of user data to customize music suggestions. Generally, a recommender system is a type of information filtering system that aims to predict users' preferences by applying algorithms and suggesting items that they might be interested in. Recommender systems analyze user behavior and employ various methods, such as collaborative filtering, content-based filtering, and hybrid approaches, to provide personalized suggestions (Bobadilla et al., 2013).

Spotify's collaborative filtering leverages user data to predict music preferences based on user similarities and their listening behaviors. This method assumes that users with past listening overlap will exhibit similar future preferences and enjoy comparable music selections (Aggarwal, 2016). Spotify's collaborative approach uses algorithms to analyze patterns of user activity, such as tracks played, playlists created, and songs skipped, to recommend music that other users with similar tastes have enjoyed (Schedl et al., 2021).

On the other hand, content-based filtering at Spotify involves analyzing the properties of music itself. This method uses audio models that examine time-frequency representations of audio files to extract features such as tempo, key, mode, time signature, and loudness. These features are then used to recommend songs sharing similar musical properties. Spotify also integrates natural-language processing to analyze lyrics and music-related content from the web. This allows Spotify to understand and utilize the context around music, such as emotional tone or thematic content, to make more nuanced recommendations that resonate with individual listeners' preferences (Shantakumari et al., 2022).

Spotify's use of advanced analytical tools transcends mere user experience enrichment. By employing a combination of collaborative filtering and content-based techniques, their recommender systems significantly influence broader music consumption trends, highlighting the profound impact of these algorithms on cultural listening patterns. By dynamically tailoring recommendations to user preferences and behaviors, Spotify fosters a highly personalized listening experience that constantly evolves.

Expansion of Musical Taste (EMT)

The expansion of musical taste refers to the broadening of user preferences and the expansion of listening habits, leading to a broader consumption of various genres and styles, therefore discovering new musical genres, artists from different cultural backgrounds, or unique and unfamiliar musical styles. This concept is closely linked to sociocultural dynamics (Eijck, 2001), personality traits (Payne, 1967), and the influence of various demographic factors (North & Davidson, 2013). However, the emergence of music streaming services has significantly amplified the potential for taste expansion (EMT) by exposing listeners to music beyond their typical choices (Tschmuck, 2012). Their algorithm-driven recommendation systems are designed to strike a balance between catering to users' existing tastes and introducing them to new songs and genres, thereby fostering EMT (Hansen et al., 2021).

Algorithm Awareness. (AA)

An algorithm, as a building block of computer science, is best understood as "a finite, abstract, effective, compound control structure, imperatively given, accomplishing a given purpose under given provisions" (Hill, 2016, p. 58). Algorithms are designed to solve entire classes of problems, not just one individual problem. They achieve this through a well-defined sequence of steps that process data. This ensures accuracy and consistency, leading to reliable and repeatable execution (Kurgalin & Borzunov, 2020).

Public comprehension of algorithms exhibits substantial variability. Despite daily interactions with algorithms on social media, search engines, and e-commerce platforms, many individuals lack a deep understanding of their underlying principles or the impact of these encounters. While research suggests a growing awareness of algorithms' presence, a profound understanding of their mechanisms and operations remains scant. Prevalent "folk theories" often depict algorithms as elusive and manipulative entities, reinforcing a sense of opacity and exploitation associated with these computational processes (Ytre-Arne & Moe, 2021). This limited understanding is likely due to the relative novelty of algorithms and their use effects, as research on public awareness of algorithmic operations is scarce (Dogruel et al., 2020; Espinoza-Rojas et al., 2022; Gran et al., 2020; Swart, 2021).

As a key term, "algorithm literacy" encompasses different aspects of what can be considered part of a deeper understanding. Swart (2021) mentions three dimensions: cognitive (awareness), affective (evaluation), and behavioral (actions). The cognitive dimension refers to the knowledge that individuals have about algorithms. It involves knowing what algorithms are, how they function, and recognizing their presence and roles in digital systems. The affective dimension relates to individuals' feelings, attitudes, and evaluations concerning algorithms. This includes the emotional responses that algorithms elicit, such as trust, fear, satisfaction, or frustration. Finally, the behavioral dimension involves the actions taken by individuals based on their understanding and emotional responses to algorithms. These dimensions are interconnected, influencing each other in various ways. For example, a deeper understanding of algorithms (cognitive) could alleviate concerns (affective), leading to more confident interactions with technology (behavioral).

For this study, the first dimension – awareness – is of primary interest. As Oeldorf-Hirsch and Neubaum (2023) pointed out, the term describes information users' knowledge that what they see or hear is personalized by dynamic systems. In the context of media content, Zarouali et al. (2021) have further specified algorithm awareness as "the extent to which people hold accurate perceptions of what algorithms do in a particular media environment, as well as their impact on how users consume and experience media content" (p.2).

Gran et al. (2021) explored algorithm awareness among Norwegians, finding that 61% of respondents felt unaware or only slightly aware of algorithms, whereas 10% felt highly knowledgeable, and a mere 3% had a very high level of awareness. Higher levels of awareness were predominantly associated with younger and more educated individuals, while older or less educated participants showed lower levels of understanding. In contrast, Dogruel et al. (2020) discovered that all participants in their study had at least a basic understanding of algorithms' roles in various online activities. Their perceptions of algorithms' impact on their autonomy varied, though: negative evaluations were noted when algorithms pushed unwanted content, whereas interactions with desired content led to a perceived lower influence of algorithms. Espinoza-Rojas et al. (2022) found that users engaging with multiple algorithm-driven platforms tended to be more aware of algorithms, especially among males and those using the platforms for acquiring knowledge. These multi-platform users proactively managed recommendations to suit their preferences, viewing mismatches as opportunities to assert control over their online interactions.

The ubiquity of recommender systems in digital platforms, including music streaming services (Spotify), video streaming devices, social media platforms, and service applications, has advanced user awareness of the algorithms shaping their experiences. Studies have demonstrated that users possess this awareness, with Facebook users acknowledging algorithmic content curation (Rader & Gray, 2015) and TikTok users employing algorithmic understanding to actively train their video feeds (Siles & Meléndez-Moran, 2021). Building on this, our study aims to investigate the role of user knowledge about Spotify's recommender systems in promoting high user engagement and facilitating musical taste expansion.

Methodology

Hypothesis and Approach

Drawing on an analysis of the above-stated theories and constructs, we formulated the following model hypothesis alongside subordinate hypotheses that measure the given variables individually:

H1: Satisfaction with Spotify's recommender system (H1a) and algorithm awareness (H1b) predict the extension in music taste among 25-34-year-olds.

Our regression model aims to identify two key predictors strongly influencing the criterion variable. Based on the literature portrayed in our theoretical framework, we expect that satisfaction with the recommender system (SRS) is a significant predictor fostering the expansion of users' musical tastes. High-quality recommender systems in music streaming services, perceived as helpful by users, will suggest new artists and genres alike. When the underlying algorithms meet the users' existing preferences and expectations, this will lead to high satisfaction with the recommender system. Given Spotify's current market leadership, we will analyze the impact of the streaming service's recommender system.

Algorithm awareness (AA) refers to the users' knowledge of the underlying principles guiding algorithms. This awareness might positively influence user evaluation and perception of the recommender system. Familiarity with an algorithm and its workings will increase user willingness to allow it to work freely within the recommender system.

Extension of music taste (EMT) will be employed as criterion in our regression model, which we aim to predict by applying the two predictors. We anticipate a positive relationship, where higher levels of both SRS and AA will lead to a greater expansion of EMT.

Survey and Questionnaire

We employed a quantitative approach through an online survey to collect data. The survey comprised 20 questions and was preceded by a short introduction outlining the study's objectives and estimated completion time. Respondents were asked to answer each question truthfully, reflecting their personal beliefs. Additionally, we ensured respondents of data confidentiality, guaranteeing anonymity and the exclusive use of responses for research purposes.

The first three questions of the survey measured the participants' age, gender, and highest level of education. The remaining 17 questions, adapted from existing, highly reliable scales, used seven-point Likert scales (1= "strongly disagree" to 7= "strongly agree") to measure predictors and the criterion variable. Questions 4 to 7 assessed participants' music taste extension (EMT) with statements such as "Spotify broadens my musical taste". These items were adapted from Krause and Brown (2021) and showed a high Cronbach's alpha of .732 (see Table 1 for all Cronbach's alphas).

Next, the participants were asked four questions (8 to 11) regarding their satisfaction with Spotify's recommender system (SRS), the first predictor in our regression. Statements such as "The music and artists recommended to me on Spotify match my interests" measured the participants' contentment and fulfillment with personalized music recommendations. The items were adapted from Pu et al. (2010) and showed a recalculated Cronbach's alpha of .742.

The final nine questions (12 to 20) measured algorithm awareness (AA) using established items from Zaraouali et al. (2021). These items, fitted to a Spotify context (e.g., "Algorithms are used to recommend music and artists to me on Spotify"), measured the predictor from various angles: content filtering, automated decision-making, human-algorithm interplay, algorithmic persuasion, and ethical considerations. All nine items demonstrated a Cronbach's Alpha of .735. Consistent with DeVellis (1991), all items exhibited satisfactory reliability, justifying their inclusion in our study.

Table 1: Cronbach's Alpha Scores for Measurement

Variable	Number of Items	Cronbach's α
EMT	4	.732
SRS	4	.742
AA	9	.735

Pretest and Data Collection

Before publishing the survey, a pre-test (n=10) was conducted, and the participants' feedback regarding comprehensibility and handling was included. In June 2023, the final survey was disseminated for one month on social media platforms such as Instagram, Facebook, and LinkedIn to reach a large sample through a voluntary response approach.

Sample

The survey targeted Spotify users aged 25 to 34, who comprise the largest demographic group, representing 29% of the platform's user base (Iqbal, 2023). This age cohort was not only among the early adopters of music streaming services but also had prior experience with music consumption before these technologies became prevalent.

To ensure statistical reliability, an a priori power analysis was conducted using G*Power, which set the significance level at .05 and the power at .80. This analysis determined that a minimum of 68 participants was necessary for the study. Ultimately, the survey collected 135 responses. However, six responses were excluded from the final analysis because they did not fall within the specified age range.

Assumptions for a Multiple Regression

In order to compute multiple regression, prerequisites need to be met. All three variables were created as continuous variables, with the predictors and the criterion showing a linear relationship. While the Shapiro-Wilk test indicated non-normal residuals ($W=0.97$, $p<.05$), our large sample size ($n=129$) allowed us to proceed with analyses based on the central limit theorem. This decision is further supported by the fact that all other key prerequisites, which have a more substantial influence if violated, were met. Tests revealed no multicollinearity (SRS and AA: VIF = 1.0, Tolerance = 1.0), no influential outliers (maximum Cook's D=.124), and no autocorrelation (Durbin-Watson = 1.88, $p>.05$). Finally, visual inspection of the residual plots, confirmed homoscedasticity.

Results

Descriptive Statistics

Responses from 129 questionnaires were considered. The data set includes participants from every age within the selected range, with the majority being 28 years old (17.2%, n=22) and a mean age of 28.3 years (SD=2.49). More participants were female (61.2%, n=79) than male (38.8%, n=50). The highest level of education showed a strong focus on participants having completed a bachelor's degree or higher (Bachelor's degree, n=46 or 35.7%; Master's degree, n=43 or 33.3%; Doctor's Degree, n=17 or 13.2%) while 14% (n=18) have a high school degree. Five respondents (3.9%) preferred not to disclose their level of education.

Regression Model

A multiple regression was conducted to investigate if SRS and AA predicted EMT. As presented in Table 2, the R^2 for the overall model was .44 (adjusted R^2=.43), indicative of a high goodness-of-fit according to Cohen (1988). This signifies that 43% of the variance in EMT can be explained by the model, which also demonstrates statistically significant predictive power ($F(2, 126)=49.8$, $p<.001$).

Table 3 presents the model coefficients and highlights the impact of each predictor on the criterion variable. Notably, the satisfaction with Spotify's recommender system (SRS) emerges as a significant predictor of music taste expansion, demonstrating a strong positive effect [ß=.66, $t(126)=9.92$, $p<.001$]. This substantial influence underscores the role of SRS in enhancing users' musical exploration.

Conversely, the participants' algorithm awareness (AA) does not significantly correlate with the expansion of their music taste. This is reflected in the model's coefficients, with a p-value of .262 indicating non-significance [ß=.0751, $t(126)=1.13$] and a relatively low B-value of 0.0939 suggesting a minimal impact of AA on users' expansion of music taste. These findings highlight the limited predictive power of algorithm awareness in influencing users' music preferences.

Table 2: Model Fit Measures

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1	.664	.441	.433	49.8	2	126	< .0001

Table 3: Model Coefficients

						95% Confidence Interval	
Predictor	**Estimate**	**SE**	**t**	**p**	**Stand. Estimate**	**Lower**	**Upper**
Intercept	1.2236	.5436	2.25	.0261			
SRS	.6759	.0681	9.92	< .0001	.6604	.5287	.792
AA	.0939	.0832	1.13	.2616	.0751	-.0567	.207

Given that the overall multiple regression model is statistically significant, we can affirmatively accept the overarching hypothesis positing that both users' satisfaction with Spotify's recommender system (SRS) and their algorithm awareness (AA) contribute to the expansion of music taste among individuals aged 25-34. The derived regression equation for this relationship is expressed as:

y=12.236 +.6759*(SRS)+.0939*(AA). This equation quantitatively models the influences of each predictor on the criterion variable.

However, while the model itself is significant, the individual contribution of algorithm awareness (AA) to the expansion of music taste is not statistically significant. This discrepancy necessitates caution in applying the model universally across different populations. The specific hypothesis related to the SRS, hypothesis H1a, can be accepted, while hypothesis H1b, which anticipated a significant effect of AA on EMT, is not supported by the data.

Discussion

Our findings indicate a positive association between user satisfaction with Spotify's recommendations and their music taste expansion (EMT). Therefore, we expect the effectiveness and accuracy of the recommender system to play a crucial role in satisfying users' preferences and encouraging the exploration of a broader range of music (artists, songs, and genres). This finding corresponds with prior research on the relationship between recommender system satisfaction and EMT. For example, Hansen et al. (2021) found that users not only appreciate recommendations based on their listening behavior but also suggestions that differ from their preferences or deviate from mainstream content recommendations. Furthermore, their findings suggest that users are more flexible in their listening behavior when interacting with music streaming services and are, therefore, more open to new music recommendations. Consequently, this flexibility allows platforms to shift consumption patterns beyond mainstream content while still satisfying users' expectations. This aligns with Villermet et al. (2021), who observed that playlists created by algorithms tend to favor unknown artists and music and intentionally avoid popular content. These findings resonate with the context of our study, as algorithmic playlists like "Discover Weekly" or "Release Radar" count as the most popular playlists on Spotify (Sharon, 2023), indicating user satisfaction with the recommendations they provide.

In contrast, a higher awareness of how algorithms operate within Spotify's recommender system did not correlate with a broader range of musical preferences. This finding indicates that even with a high level of algorithm awareness, users may not actively diversify their musical preferences, e.g., through initiating avoidance strategies. However, it is important to note that this does not imply that algorithm awareness lacks influence on other dimensions of user experience or is irrelevant overall. Rather, it indicates that within the specific context of this study, algorithm awareness does not significantly impact the music taste expansion.

Further analysis of the data reveals that participants displayed higher levels of AA on survey items predominantly addressing the essential functions of algorithms compared to more intricate mechanics. Conversely, items probing deeper into the understanding of algorithmic processes recorded lower levels of awareness. This pattern may be attributed to users' frequent interaction with surface-level functionalities of Spotify's algorithms, such as personalized recommendations, music discovery, and playlist creation, which are readily accessible to regular users. Consequently, users will likely have a more robust comprehension of these features than the complex underlying mechanisms, which remain largely opaque and confidential, with undisclosed details about datasets and decision-making processes. Thus, grasping these complexities is challenging for users without specialized knowledge in data science or algorithmic development. This limited understanding of the inner workings of the algorithms might explain why the respondents' algorithm awareness does not significantly influence music taste expansion.

Conclusion

This study investigated the research question, "To what extent does satisfaction with Spotify's recommender system and algorithm awareness predict the effectiveness in broadening the music taste among 25-34-year-olds?". While our results demonstrate that user satisfaction with Spotify's recommender system significantly predicts music taste expansion, no such relationship exists between users' awareness of the algorithms used and the expansion of their music tastes. Several factors might explain this divergence. User satisfaction could be driven by factors like trust in a recommender system that fulfills needs, increased willingness to interact with the system if it provides effective suggestions, or the system's inclination to favor content from lesser-known artists, which could be the cause of the significant prediction of music taste extension by satisfaction. At the same time, arguments like a limited knowledge of algorithms among users or the lack of algorithmic transparency could explain the non-significant relationship between algorithm awareness and music taste expansion.

Limitations

Several limitations of this study must be acknowledged. First, the sample comprised users aged 25-34 years, representing a significant demographic of Spotify users but not the entire user base. This specificity limits the generalizability of the findings to other age groups who may exhibit different usage patterns and preferences. Therefore, the representativeness of the sample and potential biases warrants careful consideration. Additionally, the voluntary response sampling method introduces another potential limitation, as self-selection bias may be present. Second, the study does not account for possible influences of cultural or regional factors, as data on participants' nationality or residence was not collected. Given that musical preferences and listening habits often vary significantly across different cultures and regions, this omission could affect the validity of the findings, potentially skewing the understanding of user interactions with Spotify's recommender system. Lastly, while the study focuses on Spotify's recommender system, it is crucial to note that each music streaming service employs unique algorithms, potentially limiting' its applicability to other platforms. Therefore, the model's effectiveness in predicting music taste expansion might differ depending on the specific platform.

Future Research

The study's findings and limitations underscore the necessity for continued research into algorithm awareness and its impact on consumer behavior across various industries that employ algorithms. As the utilization of recommender systems increases across diverse media sectors, it becomes crucial to examine their societal impacts. Future studies should aim to enhance the transparency of these systems, providing users with clearer explanations of how recommendations are generated, which could improve both algorithm awareness and user satisfaction. Further, conducting longitudinal studies with larger (probability) samples could offer valuable insights into the long-term effects of algorithm awareness and satisfaction with recommender systems on the evolution of music tastes. Additionally, exploring whether these findings hold across different digital music streaming platforms (e.g., Deezer) and video content (e.g., Netflix and YouTube) could illuminate how algorithmic design and user interface variations influence user preferences and identify best practices.

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