The impact of Spotify features on music discovery in the streaming platform age

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Abstract

Music discovery and music consumption, in general, have changed significantly in the age of digitization. Physical record stores were replaced by online music streaming platforms. This evolution changed the music industry for both consumers and artists. The music industry shifted to a subscription-based business model, offering access to immense music libraries for a monthly fee. Spotify, as the biggest music streaming service, has had a large role in this shift. The music streaming giant incorporated techniques to guide users through their enormous music catalog by offering music recommendations. Research suggests that Spotify has caused an increase in quantity and diversity of music consumption. This thesis studies the role of the different Spotify music discovery features on the perceived impact of Spotify on music discovery among students. This research applies a cross-sectional research design with an online questionnaire that was filled out by 152 respondents. Students that actively use Spotify to consume music were sampled from the population. The data was analyzed by applying the statistical analyses; Pearson's correlations, One sample T-test, and multivariate OLS-regression analyses. Two separate models were tested in the regression analyses measuring the relationship between the different Spotify music discovery features and the dependent variables measuring the perceived impact of Spotify on music discovery, and Spotify perceived as the most useful music discovery tool. The results of model 1 indicate that there is a significant positive relationship between the Spotify music discovery features discover weekly, and recommendations based on previous listening behavior and the dependent variable PSEMD. While the results of model 2 indicate that there is a significant positive relationship between the music discovery features discover weekly, recommendations based on previous listening behavior, popular playlists and the search bar, and the dependent variable PMUMDT. These results suggest that these Spotify music discovery features effect the perceived impact of Spotify on music discovery among students. With the music discovery feature, recommendations based on previous listening behavior having the strongest effect on the perceived impact of Spotify on music discovery.

KEYWORDS**:** Music discovery, Spotify features, recommendation system, music consumption, music variety

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1. Introduction

Digitization has brought a lot of change to the copyright-related industries, with the music industry as a strong example. Streaming platforms have become pivotal for audio-visual cultural consumption in this decade (Sinclair & Tinson, 2017). It is difficult to imagine a time without Netflix, Spotify, HBO, Apple Music, and others alike, while in reality, it is still a quite recent development. Digitalization has revolutionized almost every business in the world in some shape or form, this has been the case in the cultural and creative industries as well. According to Towse & Hernández (2020), digitization has brought significant changes to the cultural and creative industries regarding consumption and production. The process of digitization in the creative industries goes hand in hand with technological developments. According to Aguiar & Waldfogel (2018), the number of songs available online has tripled in the period between 2000 and 2008. The music, video game, book, and movie and TV show industries, in particular, have been revolutionized by virtue of technological innovation. More recently, a concept that has been central in the process of digitization in most creative industries has been that of platforms, more specifically, streaming platforms. Mostly in the music, film and television, and gaming industries.

So what is this phenomenon? Streaming is a technique of pushing and receiving multimedia data on modern multimedia devices. It uses the internet to make content available to users within a fraction of a second (Aguiar, 2017). Thus, it offers users of these platforms the possibility of having access to songs, albums, or an artist's entire lifework on just one small device. This effect of digitalization offers possibilities that seemed to be unimaginable just twenty years ago. While it clearly offers great benefits for consumers, the producers, in this case, artists, have reaped their share of benefits as well. Online music streaming has resulted in an increase in global music sales since the year 2015, after a decline in music sales numbers for 15 years straight (Shaw, 2018; Ingham, 2018). Moreover, it has been the most effective remedy against illegal downloading or online piracy up to this point, something that was drastically needed in this industry (Vonderau, 2019). Of course, it has not fully eliminated piracy, however as Vonderau (2019) explains, it has offered a legal and affordable substitute for the newest music releases that make illegal downloading less appealing.

When it comes to the music industry, one streaming platform has dominated the market significantly. Spotify is the largest streaming service in the industry, with 96 million paid subscribers and 170 million users overall (Field, 2020). Spotify might have changed music consumption like never before, by offering an immense music catalog to users for free. With the only downside for users being the advertising between songs. However, a premium subscription for a monthly fee of €9.99 rids users of the advertising and offers more options. Moreover, it is clear that Spotify profited from advances in technology, however, the company utilized it to its perfection. While other streaming services offer similar services, Spotify has made a name in the business with its advanced recommendation algorithm (Aguiar, 2017; Adomavicius et al., 2019). Recommendation algorithms are integrated into several platforms in the streaming industry nowadays. Platforms such as YouTube and Netflix also utilize this feature. It mostly offers consumers a shining light through an ever-growing catalog of choice in content (Adomavicius et al., 2019). Spotify has improved its recommendation system every year, with music discovery features such as the Discover Weekly playlists gaining immense popularity and reaching one billion streams in the first ten weeks after release (Jacobsen et al., 2016). Moreover, the possibility for users to generate their own playlists has become a normality regarding music consumption, with over two billion user-generated playlists in 2016 (Jacobsen et al., 2016). These features offer recorded music consumers something that was impossible a few years ago. Datta et al. (2017) illustrate how Spotify and other streaming platforms have caused an increase in the number of songs individuals consume while it also affected the variety of their music consumption. While ownership models charge per variety (different song), streaming platforms offer users the luxury of playing as many songs as they want without an additional fee. People are less inclined to listen to the same artist or song over and over again when there are no additional costs and the search costs for playing a new song are much lower compared to the record store days (Elberse, 2008).

Researchers have examined the effects of Spotify as a whole on music consumption and music discovery (Datta et al., 2017). However, Spotify has a habit of introducing new music discovery features multiple times a year. They have improved their recommendation features significantly over time. Moreover, users tend to interact with the platform in different ways. Music consumption preferences and music discovery preferences play a big role in this interaction. With Spotify offering several different music discovery features, it is interesting to dive deeper into these features. This study explores the music discovery features, or tools, that Spotify has to offer. More specifically, which of Spotify's music discovery features are mostly used on the platform, how they are ranked by users by the level of importance, and finally, what music discovery features impact music discovery on Spotify among student users. Moreover, this research aims to answer the following research question: *What Spotify music discovery features affect the perceived importance of Spotify on music discovery among students?*

Due to the large role of Spotify in the present-day music industry, the platform deserves significant academic attention. While there are several studies on the recommendation algorithm, the specific recommendation and music discovery features are left somewhat unexplored. Music consumption and music discovery preferences play a large role in an individual's everyday music listening experience. Therefore, music industry academia, as well as consumers, can benefit from understanding what influences this process specifically.

2. Theoretical framework

2.1 Quantity and variety of music consumption

Musical goods in the form of recorded songs are characterized as experience goods. According to Klein (1998), the most important attribute of experience goods is that the quality of the either too costly or too difficult to determine prior to purchase. Thus, people tend to look for signals of quality (Towse, 2010). This problem of uncertainty of quality makes a completely new musical choice quite the risk when monetary costs are involved with every single purchase. However, Spotify reduced this problem of quality uncertainty, not by removing it, but by offering the entire musical catalog for the same monthly fee. A premium subscriber is allowed to play one song, or a thousand songs, the fee remains the same for both. Therefore, the risk of playing a new song is extremely low, monetary speaking. Spotify has affected the sheer number of songs a person can listen to, however, it has affected the variety in music consumption among users as well. Datta et al. (2017) share their discoveries on music consumption after users adopted streaming platforms, where they conclude that streaming has impacted both the quantity and the diversity of music consumption in the first six months after the adoption of streaming platforms. This conclusion indicates that people tend to experiment more if the option is available to them for the same price. Which might indicate that consumers are less locked into a specific taste, but more monetarily restricted in their taste for variety.

Cultural and creative goods are said to be subject to a form of rational addiction, meaning that increased early consumption will lead to increased understanding, interest, and hence, future consumption by a consumer (Throsby, 2010; Towse, 2011). A specific cultural good can influence a person's taste formation regarding that type of good. Meaning that early exposure to a specific genre of music can have an effect on the type of music an individual enjoys. However, Towse (2011) notes how taste formation is a dynamic process that changes over time and with age. Moreover, she acknowledges how income can play a role regarding taste, as it allows consumers to explore different, yet unexplored paths. While Spotify does not affect an individual's income, it does affect the costs regarding music consumption as mentioned earlier. As a result, this might affect the individual's interest in a variety of music. In the music industry, variety in music ensures that all tastes are taken care of. The larger the quantity and variety of songs, the higher the chance that all individuals have something they can enjoy (Crain & Tollison, 2002). Which is in accordance with the notion of infinite variety properties as described by Caves (2000). Even though there is some differentiation between the goods, the difference is quite small, however, individuals can have their own reasons for their preference.

While the taste for variety is definitely a key component of the demand side in the music industry, repeat consumption is what differentiates it from other cultural industries (Handke, 2020). Which is remarkable in an industry where the supply is too large for any individual to consume. However, going back to the concept of high search costs regarding music discovery, it would make sense for users to opt for repeat listening instead of the process of finding new music (Elberse, 2008). On the supply side of the music industry, several studies have researched the emergence of superstars (Rosen, 1981; Adler, 1985). Rosen (1981) attributed the concept of a small number of artists dominating an industry and reaping the highest rewards to the discrepancies in talent between the artists. Adler (1985), however, argued that this superstar phenomenon can be attributed to the imperfect information and herd behavior, rather than a substantial difference in talent. Thus, artists that can generate high amounts of exposure and reach a certain audience, are able to strengthen the superstar phenomenon by creating an informational cascade (Adler, 1985; Bikchandani et al., 1992). Therefore, while the taste for variety is inherent in music consumption, high search costs cause consumers to use imperfect information and preferred signals to opt for less variety and more for the safe or known, choice (Elberse, 2008; Crain & Tollison, 2002).

2.2 Streaming platforms and Spotify

Streaming has become the most used format for how people consume and interact with music (Sinclair & Tinson, 2017). While it does not seem that long ago, the time of using music CD's to consume music on a large scale seems to be officially over. While popular websites such as YouTube introduced consumers to the idea of listening to music online without actually owning the recorded product, streaming platforms have made it rather normal (Sinclair & Tinson, 2017). The appeal of this access to a plethora of music listening options has also been visible in other cultural and copyright-related sectors, such as the book-publishing industry, the video game industry, and of course, the movie and TV show industries (Datta et al., 2017). According to Wayne (2018), due to the fact that streaming platforms are a quite recent technological development in the online consumption of content, it means that there is not that much known regarding the gratifications from the use of these platforms compared to the traditional channels of consumption of cultural products. However, it is evident that this shift from traditional ownership to a more access oriented business model has appealed to consumers. According to the numbers of Spotify (2019) the streaming giant and market leader, Spotify has reached 100 million paid subscribers, which leads the biggest competitor, Apple Music, by an extraordinary 50 million subscribers. Showing an impressive growth of 30% year by year. While the revenue of downloadable music and physical sales of music has dropped by respectively 10.1% and 21.2% in 2019 (IFPI, 2019). These numbers illustrate the importance and popularity of Spotify as a streaming platform for the consumption of music in 2019.

The importance of streaming platforms for the music industry is evident through the usage and subscription numbers. Hence, the reasons behind their success and popularity are an interesting topic to research, as it is also quite visible in the movie and other media industries (Dixon, 2013). The business model of the entire recording music industry has seemingly changed. The new model offers access instead of physical or online ownership of music. This development illustrates the change in the way how consumers value tangible products as opposed to the experience of consuming them (Sinclair & Tinson, 2017). The new business model of the music industry shows characteristics of the so-called long-tail model. According to Anderson (2007), the way to succeed commercially in long-tail economics has to do with a set of important rules: Firstly, make everything available two everyone and secondly, help people find what they want. Enter, Spotify. Spotify offers an online music catalog of more than 40 million songs, which might not be all of the available music in the world, however, it is in the direction of what Anderson eluded to. The other necessity, helping people to find what they want, can be awarded to the recommendation system of Spotify, which serves as a sort of guiding light among the abundance of available songs on the platform. Spotify clearly adopted the important rules that Anderson (2007) alluded to, and consumers clearly enjoy what the streaming platform has to offer.

2.3 Spotify's recommendation system and music discovery features

While Spotify might not have started the era of digitization in the music industry, one can make a strong case that they revolutionized it. As Datta, Knox, and Bronnenberg (2017) acknowledge, having access to an almost infinite number of songs has its benefits, however, it increases the search costs for new music discovery. The number of songs, albums, and artists on the platform makes it impossible to compare to the era of going to record shops and navigating their collection. Spotify came prepared for this obstacle by integrating its personalized recommendation system into the platform. While recommendation algorithms seem inherent in streaming platforms nowadays (e.g. Netflix, YouTube), Spotify has made it one of the key components of the experience on the platform. Moreover, Spotify decreases the search costs for users of the streaming platform by offering all there is to offer, while simultaneously telling users which songs and artists they might enjoy (Anderson, 2007).

The algorithm is implemented in several features across the platform, offering multiple customized listening experiences. Spotify uses personal user data to suggest songs that the user might enjoy, based on their previous interactions with music on the platform. Furthermore, Spotify recommendations come in different forms and names. Spotify offers personalized playlists for every paid subscriber of the streaming service (Adomavicius et al, 2019). These playlists can differ, they can contain songs the users play frequently or similar songs that the algorithm matches user preference based on previous listening behavior (Datta et al., 2017). One of these features and user-favorite is the 'Discover Weekly' feature. On Mondays every week, Spotify refreshes your own personal discover weekly playlist where it matches songs and artists you might enjoy based on historical listening data. Meaning that the platform can discover new artists and songs for a user, based on similar songs in the genres a user enjoys (Spotify newsroom, 2018). While other features such as 'Radio', 'Daily Mix', and 'Personalized playlists' offer a tailor-made mix of music users have interacted with before. Moreover, another popular feature is the so-called 'Release Radar' feature, where Spotify releases new music from artists that a user has interacted with on a frequent basis. It is interesting to note that some features promote repeat listening while others serve to discover new music based on the preferences of each individual user. In their conclusion, Datta et al. (2017), acknowledge that while their research does not address what exactly leads to change in music consumption, such as the increase in variety, they believe that personal recommendation features on Spotify play an important role. Table 2.1 offers an overview of all of the different music discovery features that Spotify has to offer.

While the recommendations Spotify provides are definitely considered a positive contribution to present-day music consumption, there are questions regarding this recommendation system, more precisely the algorithm it uses to recommend music. Such as is the case with Netflix, the exact mechanics behind this algorithm is protected by patent and trade secret laws and remain a public secret (Hallinan & Striphas, 2016). According to Shaw & Satariano (2016), in the past, Spotify has purposely buried songs and entire albums of artists that chose to release their new music on Apple Music, the firm's biggest competitor, making them less visible for users. This does not necessarily influence the availability of the songs, however, it does show how the company uses the platform to enhance their own interest. There have also been questions regarding the motives and even ethics behind the recommendations. As Adomavicius et al (2019) note, due to users not knowing or not realizing the effects of these recommendations, there could be not so ethical motives for recommending songs. An example can be the endorsement of a certain artist. It also leaves people wondering what kind of effect it has on the smaller artist's level of inclusion in recommendations and playlists, as opposed to the top five percent of artists. However, due to the fact that their algorithm is a public secret, most of this is still unknown. For now, it can be seen as a very consumer-friendly feature, but consumers should be wary of the effects on their preferences.

Table 2.1: Overview Spotify music discovery features

Feature	Description
Discover weekly	Discover weekly offers a new personalized playlist every Monday of the week. It matches songs from artists and genres that an user has not played before, but might enjoy.
Popular playlists	Genre based playlists which consist of popular songs of the moment. Meaning the songs that have high streaming numbers on the platform.
User-generated playlists	Playlists that are created by other Spotify users. Millions of playlists are available with new playlist being created every day.
Social media integration	The option to share songs through several social media channels. Implemented on Spotify as well as the social media applications.
Recommendations based on previous listening behavior	A category of Spotify that offers new, as well as previously consumed songs, all based on previous listening behavior. This includes the popular playlist 'Daily mix'. The recommendations are based on artists and genres that the user has played frequently.
Release radar	Release radar is similar to the discover weekly feature. Every Friday a personalized playlist is released. However, it only offers new songs from artists the user has already interacted with before.
Spotify radio	Spotify radio playlists are large playlists that contain songs from artists users listen to frequently.
Search bar	The search bar offers users the option to look up songs, artists, genres, playlists and albums whenever they want.

2.4 Network effects

Spotify has created a platform that offers access to music instead of the ownership of the physical copy. In exchange, this access offers music consumers more music than they can realistically even consume. Spotify provides this service by operating as a two-sided market platform where it serves as an intermediary between consumers and the artists providing the musical goods. Meaning that both sides directly affect each other. (Rysman, 2009). The number of people involved, on both sides of the market, affect the utility of Spotify as a streaming platform. Hence, while Spotify offers an innovative recommendation system, the streaming giant benefits greatly from the immense number of data by virtue of its many users. Therefore, a single user benefits from the presence of multiple users on the platform, as they add value through the data that they offer to Spotify. Resulting in positive network externalities from the large number of Spotify users. Spotify as a platform is fueled by network effects, which is a common characteristic of businesses that operate in multi-sided markets. Liebowitz and Margolis (1995) described network effects as changes in the benefit that an agent derives from a good or service when the number of agents that interact with the same type of good changes. These network effects can be split up into two types, direct network effects, and indirect network effects. Direct network effects, also referred to as same-side effects, entail that the value of a service increases when the number of users increases (Johnson, 2020). While this is a type of network effect is usually less applicable to platforms, Spotify does benefit from this type of network effect due to the information it collects from the interaction with its users. Meaning that users provide useful information for the recommendation algorithm (Aguiar & Waldfogel, 2018). The indirect network effect, also known as a cross-side network effect, entails that the value of a service for one group increases if an additional member joins the other group or side (Johnson, 2020). This is more common for platforms such as Spotify where consumers and producers are on opposite sides of the platform.

For Spotify, the high number of users has several benefits. Firstly, due to the rise of Spotify subscribers and users in general, global music sales have improved drastically. According to the numbers of data service Bloomberg, streaming has caused a global increase in music sales since 2015. This came after a global music sales decline of 15 years straight (Shaw, 2018). Meaning that the streaming service and its rising number of users can be considered quite appealing to artists. Moreover, Spotify has succeeded in creating a community of users. Spotify pages exist on almost all of the popular social media outlets, where people engage with each other to share playlists. Spotify subscribers can create and curate their own playlists which can be made visible to any other users of the platform. In fact, these user-generated playlists are extremely popular among users, making it one of the most used features on the platform (Forde, 2017). These playlists offer another music discovery option on the platform, by virtue of its many users. The more users use Spotify and create playlists, the more input the Spotify algorithm receives for its recommendations. Finally, as mentioned before, the possibilities to share music within your social network through the integrated social media features enables Spotify users to implement the old and reliable word of mouth communication method in a modern online setting. Overall, it seems quite unambiguous that Spotify fits the consumption theory regarding network effects. The larger the network, the greater each individual's utility is (Towse, 2010).

2.5 Music discovery

As previously discussed, Spotify has found incredible ways to contribute to new music discovery and lowering search costs in the form of time. While once upon a time the seasoned record store workers could give advice based on your music preference, they would be no match for the data-based algorithm of Spotify. In a study performed by Datta et al. (2017), the researchers used the concepts of quantity, variety, and music discovery to study the effects of Spotify on individual music consumption. The researchers constructed the data by using an anonymous third-party music recommendation service, where they randomly sampled more than 5000 recently active users from the firm's user-base and retrieved 2.5 years of consumption history data. The study applies a difference in differences approach and uses a quasi-experimental method to deal with selection effects. They conclude that streaming increased total music consumption resulted in more variety in consumption, and that it leads to more discovery of highly valued music. The researchers also conclude that Spotify increased the consumer welfare by significantly reducing the search costs involved with music variety. While it seems clear that Spotify offers a type of access to music that was inconceivable before its emergence, it is important to note that the features for music discovery (recommendation tools) on Spotify play a large role in guiding consumers through the immense music library. As previously mentioned, the writers conclude that while they cannot fully address what leads to music consumption changes, they believe that the music discovery features play an important role and recommend it for future research (Datta et al., 2017).

While the recommendation features have been discussed, the social aspect of Spotify deserves the same attention. As Mesnage et al. (2011) note, social networks have always been important in new music discovery. Word of mouth from friends, family, and other people that earn your respect has driven music discovery for ages. Spotify implemented this into its online platform as well. The platform allows users to access the profiles of friends and discover what playlists or artists they listen to. Furthermore, they integrated several social media platforms into their streaming platform. While social media apps have integrated Spotify features as well. Facebook was the first to add the feature showing your Facebook friends which song you were listening to, making it possible for friends to comment on it. While a user can also add their Instagram account to their Spotify account. Therefore allowing to directly share a song to Instagram stories. Moreover, recently Instagram made it possible to use Spotify music as the background of every Instagram story, creating a movie music effect (Perino, 2020). Spotify has shown an understanding of the importance of social networks in music sharing and hence, music discovery. The integration of social media networks in the Spotify mobile and desktop application, in combination with the music recommendation features, shows Spotify's willingness in helping the consumer navigate through the enormous music catalog. Moreover, as Datta et al. (2017) note, more music is being released due to the emergence of Spotify. The entry barriers for artists are lower, making the several possibilities for new music discovery almost essential for users to find what they want (Towse, 2011, p.301).

2.6 Hypotheses

As a result of insights gained from reviewing the literature, a set of hypotheses is formulated:

H1 = All of the Spotify music discovery features have a positive effect on the perceived strong effect of Spotify on music discovery

H2 = All of the Spotify music discovery features have a positive effect on Spotify perceived as the most useful music discovery tool

2.7 Conceptual research model

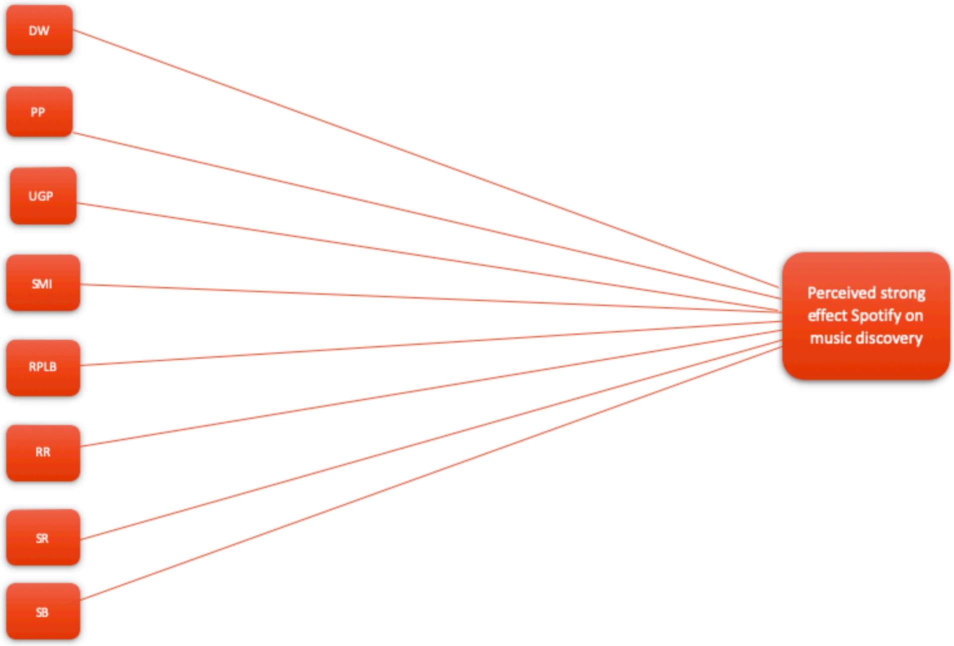

Figure 2.1: Model 1

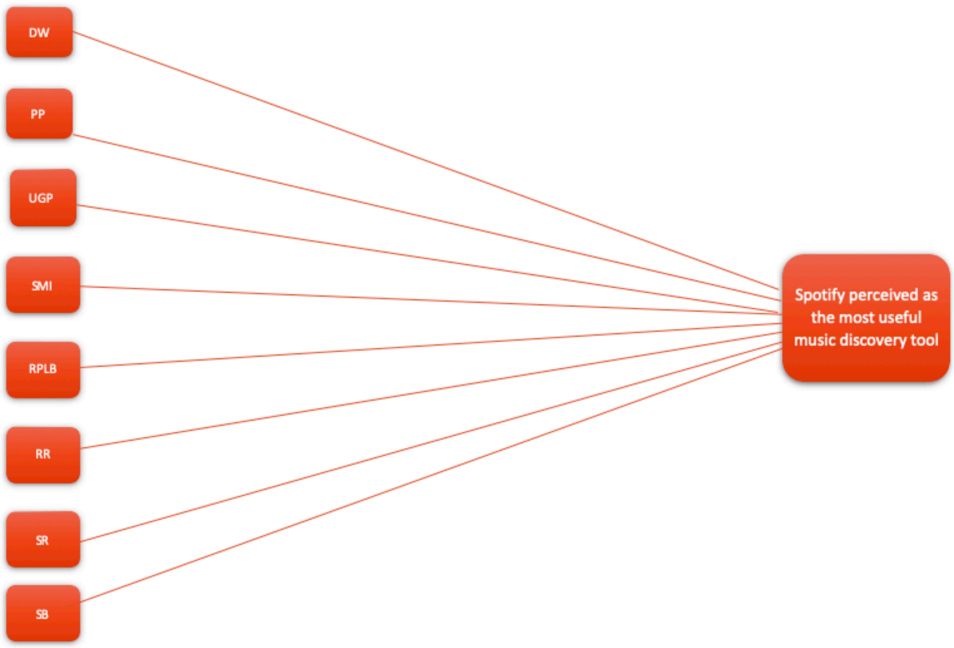

Figure 2.2: Model 2

Note: DW= Discovery weekly; PP= Popular playlists; UGP= User-generated playlists; SMI= Social media integration; RPLB= Recommendations based on previous listening behavior; RR= Release radar; SB= Search bar; SR= Spotify Radio

3. Methods

3.1 Cross-sectional research design

This research is organized as a cross-sectional design. This design is deemed as best suitable to collect the required quantitative data and establish patterns of association. The study collects quantitative data in order to gather generalizable insights (Bryman, 2016).

3.2 Research question

What Spotify music discovery features affect the perceived importance of Spotify on music discovery among students?

3.3 Research method

The research is of a quantitative nature where it studies the role of several Spotify music discovery features on the perceived impact of Spotify on music discovery among students. For this study, a survey was implemented as the research method. A online questionnaire was distributed as the main instrument of the survey research. This deductive approach will test the formulated hypotheses that are based on the literature review regarding the relevant concepts (Bryman, 2016).

3.4 Sampling

The population consists of students of the Erasmus University of Rotterdam who have used Spotify in the last year. According to data from Spotify, 55% of the users are between the age of 18 and 34 (Spotify, 2019). Moreover, Spotify offers an appealing deal for student subscriptions, offering full services of the platform for a monthly fee of $4.99 to any student attending college or University. Spotify acknowledged that their student plan has caused a rise in subscriptions. Due to the fact that the largest group of Spotify users is between 18 and 34 years of age, it matches the most common student demographic.

For this research, a form of non-probability sampling was applied due to the following restrictions; The research process started in the midst of the Corona crisis, soon the University and all the facilities shutdown as The Netherlands applied a so-called ‘intelligent lockdown’ approach. Entailing that people should only leave their residence only if necessary. During this period it was difficult to obtain a list of the units of the complete population and the sampling frame from the Erasmus University of Rotterdam. This type of personal data is confidential and students are protected by the Dutch AVG, personal data protection law. Secondly, considering the time required and the costs involved, obtaining a reliable probability sample proved too great in proportion to the available resources (Bryman, 2016).

For the sampling of the population, a snowball-sampling approach was applied. The snowball process was applied through students that represent several studies of the Erasmus University of Rotterdam, asking them forward the online questionnaire within their classes and faculty. The distribution channels that were used were Facebook and WhatsApp. 152 responses were collected by using the online questionnaire. The sampling was dependent on the kindness and willingness of Erasmus university students to participate in the study and to share the questionnaire with other EUR students inside their networks. Other individuals from the master program Cultural economics and entrepreneurship were disqualified from participating in the research in accordance with the methodological guidelines of the ESHCC faculty.

3.5 Data collection

An online questionnaire was implemented as the instrument for data collection. A description of the presented questionnaire can be found in appendix 1. The survey questionnaire was distributed by using a Qualtrics link and contacting students from different studies of the Erasmus University and asking them to share with other Erasmus University students through Facebook and WhatsApp. Other students from the master Cultural economics and entrepreneurship were eliminated from participating in the research in accordance with the methodological guidelines of the ESHCC faculty. Due to the Corona crisis circumstances the questionnaires were distributed through online channels only. Finally, there was a total of 152 respondents that completed the online questionnaire.

3.6 Operationalization

Several concepts are operationalized into variables which are used to measure data. The operationalized variables are as follows:

- *Spotify music discover features.* The following music discovery features were measured by using the same Likert scale. Moreover, all of the music discovery features were measured by using the question: How important are the following features for your new music discovery?

Discover weekly. The discover weekly variable measures the effect that the Spotify music discovery feature, discover weekly, has on the perceived impact of Spotify on music discovery among students. The data was measured by using the following liker scale options: *Not at all important - Slightly important - Neutral- Moderately important - Very important.*

Popular playlists. The popular playlists variable, measures the effect that Spotify's popular playlists (based on the number of streams) have on the perceived impact of Spotify on music discovery among students. The same Likert scale applies.

User-generated playlists. The User-generated playlists variable measures the effect that user-generated playlists have on the perceived impact of Spotify on music discovery among students. The same Likert scale applies.

Recommended based on previous listening behavior. The recommended based on previous listening behavior variable measures the effect that the playlists that Spotify recommends based on previous listening behavior, have on the perceived impact of Spotify on music discovery among students. The same Likert scale applies.

Spotify's social media integration. The Spotify's social media integration variable measures the effect that Spotify's feature of sharing music on social media and in-app friends activity has on the perceived impact of Spotify on music discovery among students. The same Likert scale applies.

Release radar. The release radar variable measures the effect that Spotify's release radar feature has on the perceived impact of Spotify on music discovery among students. The same Likert scale applies.

Spotify Radio. The Spotify Radio variable measures the effect that Spotify's radio feature has on the perceived impact of Spotify on music discovery among students. The same Likert scale applies.

Search bar. The search bar variable measures the effect that Spotify's search bar feature has on the perceived impact of Spotify on music discovery among students. The same Likert scale applies.

- *Overall Spotify music discovery impact statements.* The following statements regarding the overall impact of Spotify on music discovery were measured by the same Likert scale, asking respondents to what extent they agree with the statements.

Perceived strong effect Spotify on music discovery. The variable 'strong effect on music discovery' measures the to what extent respondents agree that Spotify has a strong effect on their music discovery. This variable is measured by posing the statement: *Spotify has a strong effect on my new music discovery.* By using a Likert-scale the following answers are possible: Strongly disagree - Somewhat disagree - Neither agree nor disagree - Somewhat agree - Strongly agree

Spotify as the perceived most useful tool for music discovery. The variable 'Spotify is the most useful tool for music discovery' measures to what extent respondents agree that for them, Spotify is the most useful tool for music discovery. This variable is measured by posing the statement: *For me, Spotify is the most useful tool for music discovery. The same Likert-scale applies.*

3.7 Data analysis

For the data analysis, multiple techniques were used. Firstly, following the univariate descriptive statistics, bivariate Pearson's correlations were analyzed to establish the associations between the variables. Secondly, a One sample T-test was used to analyze significant differences in the means of neighboring variables. Thirdly, the relationship between the multiple independent and the two dependent variables was analyzed by using a linear OLS-regression analysis, more specifically a multivariate OLS-regression analysis. This type of analysis allows for statistical analysis of the relationship between the dependent variable and multiple independent variables (Salkind & Frey, 2019). Finally, the relationship between the several demographic variables, and the different Spotify music discovery features was analyzed.

It is important to note that for the data analyses, the Likert scale variables were treated as continuous variables. Due to the ordinal nature of likert-scale variables and the numerical data required for the analyses, we treat the variables as if they were continuous. A practice that is quite common in the social sciences (Hair et al., 2003). This limitation is acknowledged for the interpretation of significant results.

3.8 Research weaknesses

Due to time, financial, and the Corona crisis restrictions, non-probability sampling was applied as discussed in previous sections. Therefore, it would be difficult to generalize these results to the entire population. However, future research on this topic might benefit from the concepts and operationalization of the variables of this research.

It should be noted that while this research studies impact, it does not observe direct relevant behavior. It requires participants of the study to use recollections of their behavior to the best of their ability.

3.9 Descriptive statistics

Table 3.1 illustrates the mean, range and standard deviation of the dependent and independent variables for all the respondents of this sample (N = 152). Regarding the independent variables measuring the perceived importance of the several Spotify music discovery features, table 3.1 shows that on a range from 0 to 5, the search bar (m = 4.17) was perceived to be the most important music discovery feature on Spotify. Scoring slightly higher on average than the recommendations based on previous listening behavior (m = 4.05). The importance of the discover weekly feature (m = 3.57) and user-generated playlists (m = 3.57) was perceived to be higher than the popular playlists (m = 3.07), release radar (m = 3.09), Spotify radio (m = 3.03) and social media integration (m = 2.59). Illustrating that on average, the social media integration is perceived as the least important Spotify music discovery feature among this sample.

In regards to the first dependent variable, measuring to what extent respondents agreed that Spotify has a strong effect on their new music discovery, table 3.1 illustrates that on a range from 1 to 5, respondents on average perceived the effect of Spotify on their new music discovery to be relatively strong (m = 4.02). Regarding the second variable, measuring to what extent respondents agreed that Spotify is the most useful tool for new music discovery, on a range from 1 to 5, respondents on average rated Spotify as the most useful tool for new music discovery relatively high (m = 3.92). Both of the dependent variables show a relatively low SD (SD = 0.95, SD = 0.96), indicating that the answers were relatively close to the mean.

Table 3.1: Descriptive statistics (N=152)

Variable	Description	Mean	Range	SD	Min.	Max.
Search bar	The importance of the Search bar feature on music discovery	4.17	5	1.17	0	5
Recommendations based on previous listening behavior	The importance of the Previous listening behavior recommendations on music discovery	4.05	5	1.09	0	5
Discover weekly	The importance of the Discover weekly feature on music discovery	3.57	5	1.35	0	5
User-generated playlists	The importance of the User-generated playlists feature on music discovery	3.57	5	1.43	0	5
Release radar	The importance of the Release radar feature on music discovery	3.09	5	1.55	0	5
Popular playlists	The importance of the Popular playlists feature on music discovery	3.07	5	1.39	0	5
Spotify radio	The importance of the Spotify radio feature on music discovery	3.03	5	1.49	0	5
Social media integration	The importance of the Social media integration feature on music discovery	2.59	5	1.53	0	5
Perceived effect of Spotify on music discovery	Rating of The effect of Spotify on users new music discovery	4.02	4	0.95	1	5
Spotify as the perceived most useful tool for music discovery	Rating of Spotify as the most useful tool for music discovery	3.92	4	0.96	1	5

Table 3.2 illustrates the mean, standard deviation and the range of the demographic profile of the sample. In regards to the frequencies, gender is favored towards women with 65.1% being female while 34.9% is male. 76.3% of the respondents are in the age group of 20-25 years old, while 20.4 % are between 26 and 30 years old. 60.5% of the respondents have the Dutch nationality while 39.5% filled out they do not. Regarding disposable income, the largest group is between €500 and €1000, 25.7%. While, 5.9% is less than €100, 24.3% between €100 and €500, 18.4% between €1000 and €2000, 16.4% more than €2000. Finally, the educational level, 59.2% of the respondents were at a bachelor level. While 34.2% were at a master level and 5.9% was pre-master.

Table 3.2: Descriptive statistics demographics (N=152)

Variable	Mean	Range	SD	Min.	Max.
Gender (1 = Female; 2 =Male)	1.35	1	0.478	1	2
Age (1 = 20-25; 2 = 26-30; 3 = 31-35)	1.25	2	0.477	1	3
Nationality (1 = Dutch; 2 = Non-Dutch)	1.39	1	0.490	1	2
Highest level of education (1 = Bachelor; 2 = Pre-master; 3 = Master; 4= PhD)	1.76	3	0.954	1	4
Disposable income (0= prefer not to say; 1 =< €100; 2 = €100-€500; 3 = €500-€1000; 4=€1000-€2000; 5= >€2000	3.43	5	1.408	1	6

4. Analysis and results

4.1 Pearson's correlations

Table 4.1 illustrates the results and significance levels of the Pearson correlations for all the independent variables regarding the level of importance of the several Spotify features, and the dependent variables; the overall rating of Spotify as the perceived most useful tool for music discovery and the rating of the perceived strong effect of Spotify on music discovery Regarding the two dependent variables, the overall rating of Spotify perceived as the most useful music discovery tool (PMUMDT) and the rating of Spotify's perceived strong effect on music discovery (PSEMD), there is a strong, positive significant linear association found between them, $r(150) = 0.741$, $p= 0.01$. Meaning that the answers to these questions are strongly correlated.

In regards to the association between the independent variables and the dependent variable; Perceived strong effect of Spotify on music discovery (PSEMD), there is a positive and significant linear association found for the discover weekly $r(150) = 0.326$, $p= 0.01$ (DW), popular playlists $r(150) = 0.237$, $p= 0.01$ (PP), recommendations based on previous listening behavior $r(150) = 0.352$, $p= 0.01$ (RPLB), release radar $r(150) = 0.236$, $p= 0.01$ (RR) and the search bar $r(150) = 0.201$, $p= 0.05$(SB). Although these associations can be considered relatively weak.

In regards to the association between the independent variables and the dependent variable; Spotify perceived as the most useful music discovery tool (PMUMDT), there is a positive significant linear association found for discover weekly $r(150) = 0.285$, $p= 0.01$ (DW), recommendations based on previous listening behavior $r(150) = 0.332$, $p= 0.01$ (RPLB), release radar $r(150) = 0.236$, $p= 0.01$ (RR), and Spotify radio $r(150) = 0.195$, $p= 0.05$ (SR). Although these associations can also be considered relatively weak.

The strongest association between independent variables is found between discover weekly (DW) and release radar (RR), $r(150) = 0.420$, $p= 0.01$. Indicating a positive significant but weak association.

Table 4.1: Correlation matrix dependent and independent variables (N=152)

	SEMD	MUM-DT	DW	PP	UGP	SMI	RPLB	RR	SB	SR
PSEMD	1	0.741**	0.326**	0.237**	0.125	0.068	0.352**	0.236**	0.201*	0.122
PMUMDT	0.741**	1	0.285**	0.064	0.128	0.110	0.332**	0.250**	0.110	0.195*
DW	0.326**	0.285**	1	0.209**	0.288**	0.282**	0.194*	0.420*	0.085	0.050
PP	0.237**	0.064	0.209*	1	0.245**	0.125	0.191*	0.191*	-0.93	0.053
UGP	0.125	0.128	0.288**	0.245**	1	0.320**	0.286**	0.302*	0.192*	0.203*
SMI	0.068	0.110	0.282**	0.125	0.320**	1	0.226**	0.255**	0.014	0.266**
RPLB	0.352**	0.332**	0.194*	0.191*	0.286**	0.226**	1	0.151	0.135	0.146
RR	0.236**	0.250**	0.420**	0.191*	0.302**	0.255**	0.151	1	0.175*	0.131
SB	0.201*	0.110	0.085	-0.093	0.192*	0.014	0.135	0.175*	1	0.088
SR	0.122	0.195*	0.050	0.053	0.203*	0.266**	0.146	0.131	0.088	1

N=152 *p <0.5; ** p<0.01

PSEMD= Perceived strong effect music discovery; PMUMDT= Perceived most useful tool music discovery; DW= Discovery weekly; PP= Popular playlists; UGP= User-generated playlists; SMI= Social media integration;
RPLB= Recommendations based on previous listening behavior; RR= Release radar; SB= Search bar; SR= Spotify Radio

4.2 One sample T-test neighboring variables

Table 4.2 depicts the results of the one sample T-test for comparing means between the several Spotify music discovery features. The T-test indicates if there are significant differences in the means of the neighboring music discovery feature variables. Meaning that every variable mean is compared with the next variable mean in order of their rank. The variables are ranked by their mean as illustrated in table 4.1. This approach produced seven separate T-tests which are described in table 4.2. Looking at the significance levels, the means of the recommendations based on previous listening behavior and discover weekly differ significantly MD = 0.476, p = 0.001. Regarding the mean of the user-generated playlists and the mean of the release radar feature, there is a significant difference found between them MD = 0.476, p = 0.001. The means of popular playlists and Spotify radio prove to be significantly different as well MD = 0.751, p= 0.036. Finally, regarding the means of Spotify radio and social media integration, there is a significant difference found between them, MD = 0.443, p = 0.001. The difference between the means of the other music discovery feature variables, did not prove to be statistically significant.

Table 4.2: One sample T-test Spotify music discovery features (N=152)

Variable	Mean	t	Mean difference	Sig.	Test value
Search bar	4.17	1.279	0.121	0.203	4.05
Recommendations based on previous listening behavior	4.05	5.395	0.476	0.001	3.57
Discover weekly	3.57	0.022	0.002	0.983	3.57
User-generated playlists	3.57	4.112	0.476	0.001	3.09
Release radar	3.09	0.124	0.016	0.902	3.07
Popular playlists	3.07	0.318	0.751	0.036	3.03
Spotify radio	3.03	3.656	0.443	0.001	2.59
Social media integration	2.59	-	-	-	-

4.3 Multivariate OLS-regression analysis

In this chapter, the results of the multivariate linear regression analysis are presented in tables 4.3 and 4.4. These statistical analyses have been utilized to test two separate models. Furthermore, the relationship between the several independent variables and the one dependent variable for each model is tested. This analysis was used for several reasons. Firstly, to indicate if there is a significant relationship between the dependent variable and the independent variables. Secondly, to determine the amount of variance in the dependent variables predicted by the independent variables.

4.3.1 Multivariate OLS-regression analysis model 1

Table 4.3 illustrates the results of the multivariate OLS-regression analysis for model 1. This analysis tests the relationship between independent variables regarding the several Spotify music discovery features and the dependent variable, perceived strong effect of Spotify on music discovery (PSEMD). Model 1 of table 4.3 informs us that there is no significant link found between gender and Spotify's perceived strong effect on music discovery ($b = 0.176$, $p > 0.05$). The results suggest that there is a significant and positive link between the Discover Weekly feature and the perceived strong effect Spotify on music discovery ($b = 0.152$, $p < 0.01$). Meaning that if the discover weekly feature increases with one unit, the perceived strong effect of Spotify on music discovery increases with a factor of 0.152. Moreover, the popular playlists feature does not significantly predict the perceived strong effect of Spotify on music discovery ($b = -0.023$, $p > 0.05$). In regards to the following feature, the user-generated playlist feature does not significantly predict the perceived strong effect of Spotify on music discovery ($b = -0.036$, $p > 0.05$). Regarding the following feature, the social media integration feature does not significantly predict the perceived strong effect of Spotify on music discovery ($b = -0.046$, $p > 0.05$). We find that the recommendations based on previous listening behavior feature is significantly positively linked with the perceived strong effect of Spotify on music discovery ($b = 0.260$, $p < 0.001$). Meaning, that if the recommendations based on previous listening behavior feature increases with one unit, the perceived strong effect of Spotify on music discovery increases with a factor of 0.260. Regarding the following feature, the release radar feature does not significantly predict the perceived strong effect of Spotify on music discovery ($b = 0.080$, $p > 0.05$). Regarding the following feature, the search bar feature does not significantly predict the perceived strong effect of Spotify on music discovery ($b = 0.020$, $p > 0.05$). Finally, regarding the last music discovery feature, the release radar feature does not significantly predict the perceived strong effect of Spotify on music discovery ($b = 0.099$, $p > 0.05$). Thus, we fail to reject the null-hypothesis that states that all of the Spotify music discovery features have a positive effect on the perceived strong effect of Spotify on music discovery. Only discover weekly and recommendations based on previous listening behavior a significant and positive relationship with the perceived strong effect of Spotify on music discovery.

Assessing the adjusted R^2 coefficient, we find that this model significantly explains 21.8% of the found variance that predicts the perceived strong effect of Spotify on music discovery (Adjusted $R^2 = 0.218$).

Table 4.3: Multivariate OLS-regression analysis music discovery features model 1 (N=152)

	Model 1	
	B	S.E.
Perceived strong Spotify effect music discovery (constant)	1.877***	0.480
Gender	0.176	0.153
Discover weekly	0.152**	0.061
Popular playlists	-0.23	0.055
User-generated playlists	-0.36	0.058
Social media integration	-0.46	0.052
Recommendations based on previous listening behavior	0.260***	0.071
Release radar	0.080	0.053
Search bar	0.020	0.064
Spotify radio	0.099	0.050
Adjusted R^2	0.218	

N = 152 ***p<0.001, **p<0.01, *p<0.05

4.3.2 Multivariate OLS-regression analysis model 2

Table 4.4 illustrates the results of the multivariate OLS-regression analysis for model 2. This analysis tests the relationship between independent variables regarding the several Spotify music discovery features and the dependent variable, Spotify perceived as the most useful music discovery tool. Table 4.4 informs us that there is no significant link found between gender and Spotify perceived as the most useful music discovery tool ($b = 0.1158$, $p > 0.05$). We find that the discover weekly feature is significantly positively linked with Spotify perceived as the most useful music discovery tool ($b = 0.180$, $p < 0.01$). Meaning that if the discover weekly feature increases with one unit, the rating of Spotify perceived as the most useful music discovery tool increases with a factor of 0.180. Regarding the following feature, popular playlists, we find that popular playlists is significantly positively linked with Spotify perceived as the most useful music discovery tool ($b= 0.121$, $p < 0.05$). Indicating that if the discover weekly feature increases with one unit, the rating of Spotify perceived as the most useful music discovery tool increases with a factor of 0.121. In regards to the following music discovery feature, the user-generated playlists feature does not significantly predict Spotify as the most useful tool for music discovery as perceived by respondents ($b= -0.069$, $p > 0.05$). Regarding the following feature, Social media integration does not significantly predict Spotify perceived as the most useful music discovery tool ($b= -0.023$, $p > 0.05$). We find that the recommendations based on previous listening behavior is significantly positively linked with Spotify perceived as the most useful music discovery tool ($b= 0.257$, $p < 0.001$). Meaning that if the recommendations based on previous listening behavior increases with one unit, the rating of Spotify perceived as the most useful music discovery tool increases with a factor of 0.257. Moreover, the release radar feature does not significantly predict Spotify perceived as the most useful music discovery tool ($b= -0.023$, $p > 0.05$). Regarding the search bar feature, we find that the search bar feature is significantly positively linked with Spotify perceived as the most useful music discovery tool ($b= 0.131$, $p < 0.05$). Meaning that if the search bar increases with one unit, the rating of Spotify perceived as the most useful music discovery tool increases with a factor of 0.131. Finally, regarding the Spotify radio feature, we find that Spotify radio does not significantly predict Spotify perceived as the most useful music discovery tool ($b= 0.053$, $p > 0.05$). Thus, we fail to reject the null-hypothesis that states that all of the Spotify music discovery features have a positive effect on Spotify perceived as the most useful music discovery tool. Only discover weekly, popular playlists, recommendations based on previous listening behavior, and the search bar have a significant and positive relationship with Spotify perceived as the most useful music discovery tool.

Assessing the adjusted R^2 coefficient, we find that this model significantly explains 15.4% of the found variance that predicts Spotify perceived as the most useful music discovery tool (Adjusted $R^2 = 0.154$).

Table 4.4: Multivariate OLS-regression music discovery features model 2 (N=152)

	Model 2	
	B	S.E.
Spotify perceived as the most useful music discovery tool (constant)	1.228**	0.467
Gender	0.158	0.149
Discover weekly	0.180**	0.059
Popular playlists	0.121*	0.053
User-generated playlists	-0.069	0.056
Social media integration	-0.064	0.051
Recommendations based on previous listening behavior	0.257***	0.069
Release radar	0.043	0.052
Search bar	0.131*	0.062
Spotify radio	0.053	0.049
Adjusted R^2	0.154	

N= 152 ***p<0.001, **p<0.01, *p<0.05

4.4 Multivariate OLS-regression analyses demographics

In order to test the relationship between the demographic variables and the Spotify music discovery features, 8 separate multivariate OLS-regression analyses were performed. By analyzing this data we can establish what demographic appropriates a specific Spotify music discovery feature.

By assessing the coefficients in tables 4.5 til 4.12, we find that none of the demographic variables are significant predictors of the Spotify music discovery features. Not one single variable was significantly linked. Moreover, we find that the F-test indicates that none of the models were significant. Suggesting that according to the data, the demographics do not significantly affect the importance of the Spotify music discovery features.

Table 4.5: Multivariate OLS-regression demographics and discover weekly (N=152)

	B	S.E.
Discover weekly (constant)	3.645***	0.611
Gender	-0.327	0.234
Age groups	0.027	0.257
Nationality	0.208	0.237
Highest level of education	-0.035	0.121
Disposable income	-.042	0.084
Adjusted R^2	0.020	

N= 152 ***p<0.001, **p<0.01, *p<0.05

Table 4.6: Multivariate OLS-regression demographics and popular playlists (N=152)

	B	S.E.
Popular playlists (constant)	3.726***	0.632
Gender	-0.432	0.242
Age groups	0.228	0.266
Nationality	-0.036	0.245
Highest level of education	-0.037	0.125
Disposable income	-.082	0.087
Adjusted R^2	-0.003	

N= 152 ***p<0.001, **p<0.01, *p<0.05

Table 4.7: Multivariate OLS-regression demographics and user-generated playlists (N=152)

	B	S.E.
User-generated playlists (constant)	2.460***	0.636
Gender	-0.319	0.244
Age groups	0.020	0.268
Nationality	0.526	0.247
Highest level of education	0.227	0.126
Disposable income	0.127	0.088
Adjusted R^2	0.033	

N= 152 ***p<0.001, **p<0.01, *p<0.05

Table 4.8: Multivariate OLS-regression demographics and social media integration (N=152)

	B	S.E.
Social media integration (constant)	1.604*	0.684
Gender	0.127	0.262
Age groups	-0.323	0.288
Nationality	0.491	0.265
Highest level of education	0.290	0.135
Disposable income	0.004	0.094
Adjusted R^2	0.027	

N= 152 ***p<0.001, **p<0.01, *p<0.05

Table 4.9: Multivariate OLS-regression demographics and recommendations based on previous listening behavior (N=152)

	B	S.E.
Recommendations based on previous listening behavior (constant)	4.096***	0.492
Gender	-0.391	0.189
Age groups	0.062	0.207
Nationality	0.052	0.191
Highest level of education	0.102	0.097
Disposable income	0.050	0.068
Adjusted R^2	0.005	

N= 152 ***p<0.001, **p<0.01, *p<0.05

Table 4.10: Multivariate OLS-regression demographics and release radar(N=152)

	B	S.E.
Release radar (constant)	2.704***	0.712
Gender	0.085	0.273
Age groups	-0.270	0.300
Nationality	0.151	0.276
Highest level of education	0.079	0.141
Disposable income	0.087	0.098
Adjusted R^2	-0.024	

N= 152 ***p<0.001, **p<0.01, *p<0.05

Table 4.11: Multivariate OLS-regression demographics and search bar (N=152)

	B	S.E.
Search bar (constant)	4.456	0.531
Gender	-0.045	0.204
Age groups	0.231	0.223
Nationality	-0.301	0.206
Highest level of education	-0.082	0.105
Disposable income	0.017	0.073
Adjusted R^2	-0.003	

N= 152 ***p<0.001, **p<0.01, *p<0.05

Table 4.12: Multivariate OLS-regression demographics and Spotify radio (N=152)

	B	S.E.
Spotify radio (constant)	2.779***	0.670
Gender	0.094	0.257
Age groups	-0.455	0.282
Nationality	0.388	0.260
Highest level of education	0.118	0.133
Disposable income	-0.005	0.093
Adjusted R^2	0.003	

N= 152 ***p<0.001, **p<0.01, *p<0.05

5. Discussion and conclusion

This thesis focusses on music discovery in the streaming platform age. As a consequence of digitization and technological progress, music consumption and music discovery have drastically evolved in a span of ten years. This evolution has inspired Spotify while simultaneously, Spotify has impacted this evolution. After reviewing the literature on this topic, the popularity of the different Spotify music discovery features or tools stood out. The literature review of this topic suggested that the popularity and importance of Spotify's music discovery features (recommendation tools) might have a large part in the music discovery and music consumption changes. The aim of this thesis was to research the role and the importance of the several Spotify music discovery features in relation to the perceived impact of Spotify on music discovery among students. In doing so, the different music discovery features were analyzed in a univariate matter, as well as a bivariate and multivariate manner.

The descriptive statistics in table 3.1 inform us that in regards to the level of importance of the several music discovery features on Spotify regarding music discovery, the search bar, recommendations based on previous listening behavior, discover weekly and user-generated playlists score the highest among the respondents. Moreover, while respondents tend to rate other recommendation based features relatively high, the search bar feature is deemed the most important one. Indicating that people prefer to have the option to look up music on their own, meaning without Spotify offering the recommendation. The feature, recommendations based on previous listening behavior, is right behind the search bar in the level of importance. However, this feature has the lowest standard deviation out of all the music discovery features, indicating that the answers did not differ too much from the mean. The two dependent variables measuring the perceived impact of Spotify on music discovery, and the perceived usefulness of Spotify as a music discovery tool, both scored relatively high. Indicating that respondents tend to agree that Spotify has an impact on their music discovery.

In the first data analysis, the Pearson's correlations illustrated in table 4.1, we analyze the association between all of the dependent and independent variables. We find that the two dependent variables PSEMD and PMUMDT are strongly and positively correlated. Suggesting that there is a strong relationship between the two variables. All the other significant positive associations between the variables were relatively weak. The One sample T-test reported in table 4.2, was performed to test statistically significant differences in the means of the neighboring variables (ordered by rank). The highest-rated variable mean, that of recommendations based on previous listening behavior, significantly differed from the neighboring variable mean, discover weekly. Indicating that the recommendations based on previous listening behavior is rated significantly higher than the discover weekly feature. The same can be said about the difference in means of user-generated playlists compared to release radar, popular playlists compared to the Spotify radio feature, and of Spotify radio compared to social media integration. With the former being rated significantly higher than the latter in each case.

Tables 4.3 and 4.4 report the findings from the multivariate OLS-regression analyses, in which two models are tested. Firstly, the relationship between the multiple music discovery features and the perceived strong effect of Spotify on music discovery is analyzed. Table 4.3 provides empirical support that the feature recommendations based on previous listening behavior has the highest positive impact on the perceived strong effect of Spotify on music discovery. Indicating that respondents were significantly more likely to rate Spotify has a strong effect on music discovery if they considered the recommendations based on previous listening behavior feature an important music discovery feature. The control variable, gender, did not prove to be a significant predictor of the dependent variable. By assessing model 1, we find that 21.8% of the perceived impact of Spotify on music discovery can be predicted by the music discovery features.

Secondly, the relationship between the multiple music discovery features and Spotify perceived as the most useful music discovery tool is analyzed. Table 4.4 provides empirical support that the feature recommendations based on previous listening behavior has the highest positive impact on Spotify perceived as the most useful music discovery tool. Indicating that respondents were significantly more likely to rate Spotify as the most useful tool for music discovery if they considered the recommendations based on previous listening behavior feature an important music discovery feature. Once again, the control variable, gender, did not prove to be a significant predictor of the dependent variable. By assessing model 2, we find that 15.4% of Spotify perceived as the most useful music discovery tool can be predicted by the music discovery features. Tables 4.5-4.12 illustrate the results of the relationship between the demographic variables and the different Spotify music discovery features. There was no significant relationship found.

For the implications of this study and for possible future research on this topic, it is important to indicate the limitations of this research. Firstly, as described in the methods chapter, the sampling of the population for this study has been done using the snowball-sampling approach. Entailing that the sample may or may not represent the population correctly. Therefore, we cannot make generalizations pertaining to the entire population. Future research could benefit greatly from probability sampling. Secondly, the measured perceived impact is not directly observed, it rather relies on the recollections of respondents. This makes it impossible to speak of a causal relationship between the Spotify music discovery features and the impact of Spotify on music discovery. Future studies on this topic could benefit greatly from using a longitudinal or experimental design which would allow us to find causal relations between the variables. Thirdly, to make the data applicable for the regression analyses, this study treats the Likert scale variables as numerical data. This is not uncommon in the social sciences, however, it should be considered controversial.

To conclude, as the literature suggests, Spotify has had a significant impact on music discovery and music consumption in general. This study explores the importance of the specific music discovery features on the platform. The study answers the question: What Spotify music discovery features affect the perceived importance of Spotify on music discovery among students? The music discovery features discover weekly and recommendations based on previous listening behavior have a positive significant relationship with the perceived impact of Spotify on music discovery. Moreover, the results indicate that recommendations based on previous listening behavior has the strongest effect on the perceived impact of Spotify on music discovery. While there are other factors that influence variety in consumption, such as lower search costs and no additional fees involved in playing a different song, Spotify's music discovery features are perceived as important in new music discovery. The theory suggests that they help deal with the search costs involved in exploring a plethora of musical choices. Finally, the role of these Spotify music discovery features in regards to song, album, or artist success could be a fruitful area for future research. As these music discovery features are utilized frequently to consume music, the scientific community as well as practitioners could benefit from further research regarding the consequences for the music industry in this streaming platform age.

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Appendix: Survey questionnaire

Introduction

Block Options

Q1

I would like to thank you for participating in this questionnaire for my thesis for the Master Cultural Economics and Entrepreneurship at Erasmus University Rotterdam. This research is about the new music discovery process in the age of Spotify. The study aims to uncover and understand what influences the discovery of new music among Spotify users.

When completing the survey, you are giving consent to use the results for the master thesis only. Participation is anonymous and after completion of the thesis, the results will be deleted. Only the thesis will be archived.

I would also like to remind you that your participation is completely voluntary and you may stop the survey at any time.
1. By filling out this survey you indicate that: you are at least 18 years of age; An Erasmus University student; Use Spotify to listen to music; You have read and agree to terms explained on this page, and, you voluntarily choose to participate in this research.
2. If you are not at least 18 years of age or do not agree with the terms of this survey, please exit the survey.

If you have any questions regarding the survey, please feel free to contact me at **514882ds@student.eur.nl**.

Thank you for participating in this survey!

Q1

What is your Gender?

- Female
- Male
- Non-Binary

Q2

What is your age?

Q3

Do you have the Dutch nationality?

- Yes
- No

Q4

What is the highest level of education you have completed?

Note: *If you are currently studying, please select the option in which you are currently enrolled.*

- Bachelor
- Pre-Master
- Master
- Doctorate (PhD)

Q5

What is your average monthly disposable income?

Note: Income after taxes available to be spent as you wish.

- Less than €100
- €100 - €500
- €500 - €1000
- €1000 - €2000
- More than €2000
- I prefer not to say

Spotify subscription

Block Options

Q6

Have you used the streaming platform Spotify to listen to music in the last year?

- Yes
- No

Q7

Are you currently a Spotify premium subscriber?

Note: Either type of user is included in the survey.

- Yes
- No

Display This Question:

If Are you currently a Spotify premium subscriber? Note: Either type of user is included in the su... Yes Is Selected

Q8

How satisfied are you with your Spotify Premium subscription?

Very dissatisfied	Dissatisfied	Neither satisfied nor dissatisfied	Satisfied	Very satisfied
○	○	○	○	○

Q9

Over the last four weeks, how often have you used Spotify?

None	One time	2-3 times	Once a week	Multiple times a week	Everyday
○	○	○	○	○	○

Q10

On average, would you say this is a normal month of musical consumption for you?

- Yes
- No

Q11

Over the last week, how many hours a day did you listen to music on Spotify?

Less than 1 hour a day	1-2 hours	2-3 hours	3-4 hours	More than 5 hours a day
○	○	○	○	○

Q12

On average, would you say this is a normal day of musical consumption for you?

- Yes
- No

Music consumption preferences Block Options

Q13

Below you will find several statements about your specific music consumption habits and preferences. Please indicate to what extent you agree with the following statements:

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree	I do not know
I constantly try to discover music that I am not familiar with	○	○	○	○	○	○
I like to listen to music from very different artists	○	○	○	○	○	○
I like to listen to music from very different genres	○	○	○	○	○	○
I like to listen to the same music over and over again	○	○	○	○	○	○
I like to be up-to-date about recently released music	○	○	○	○	○	○
I like to search for new music on my own	○	○	○	○	○	○
I like to hear about new music that I can listen to from others	○	○	○	○	○	○

Spotify as a music discovery tool Block Options

Q14

Please indicate to what extent you agree with the following statements

	Strongly disagree	Somewhat disagree	Neither agree or disagree	Somewhat agree	Strongly agree
For me, Spotify is the most useful tool for new music discovery	○	○	○	○	○
Spotify has a strong effect on my new music discovery	○	○	○	○	○

Q15

How satisfied are you with new music discovery on Spotify?

Very dissatisfied	Dissatisfied	Neither satisfied nor dissatisfied	Satisfied	Very satisfied
○	○	○	○	○

Q16

This section is about the importance of several Spotify related features for new music discovery.

How important are the following Spotify features for your new music discovery?

	Not at all important	Slightly important	Neutral	Moderately important	Very important	I do not know this feature
The Spotify feature 'Discover Weekly'	○	○	○	○	○	○
Spotify's 'Popular playlists'	○	○	○	○	○	○
Spotify's 'User-generated playlists' (public playlists created by other users)	○	○	○	○	○	○
Spotify's social media integration (seeing Spotify music on your social media channels)	○	○	○	○	○	○
Spotify recommendations based on your previous listening behavior (this includes 'Daily Mix')	○	○	○	○	○	○
Spotify's 'Release radar' feature	○	○	○	○	○	○
The Spotify search bar option	○	○	○	○	○	○
The Spotify 'Radio' feature	○	○	○	○	○	○

Display This Question:

If This section is about the importance of several Spotify related features for new music discovery.... - Very important Is Selected

Q17

You have reported that one or more feature(s) is very important for your music discovery. Could you please briefly describe why it is very important to you regarding your new music discovery?