Do they *Discover Weekly* your taste?

The differences between heavy and light users of Spotify

Student Name: Katarzyna Derwinis
Student Number: 507322

Supervisor: Dr. Joao Ferreira Goncalves

Master Media Studies - Media & Creative Industries
Erasmus School of History, Culture and Communication
Erasmus University Rotterdam

Master's Thesis
June 2020

Do they *Discover Weekly* your taste?

ABSTRACT

The expansion of the streaming services and new media has led to overwhelming catalogues of content available online. One of the most popular music streaming platforms that offers a broad collection of music on demand is Spotify. To facilitate the music discovery, this service provides its users with algorithmically created Discover Weekly playlist, that allows exploring new content every Monday morning. Moreover, these algorithmically created recommendations have a significant potential to facilitate discovering of new music that users are not familiar with. However, recommendation systems are also perceived to decrease diversity as they keep users in filter bubbles and echo chambers, where they are exposed to similar content. How users of the service perceive the diversity of their music content may be dependent on characteristics as subscription model or the quantity of music consumed daily. As People that spend more time on exploring the Internet and new technologies are perceived to be heavy users. In contrary, when they are less active online, they can be categorized as the light users. This assumption was used concerning music listening through the streaming platform, Spotify. Therefore, this thesis aims to analyse whether the differences in Spotify usage have an impact on the perceptions of the algorithmically created playlist, Discover Weekly. Thus, the research question was asked: to what extent does the diversity of the music recommended by the Discover Weekly playlists differ between heavy and light users of Spotify? To answer the main research question six hypotheses regarding music diversity, algorithmic recommendations and algorithmic satisfaction were stated. To be able to measure the differences between heavy and light users, the quantitative surveys were conducted. With the use of gathered data from 359 Spotify users, the outcomes were examined with the use of statistical tests and the SPSS software. The analysis indicated that there are no significant differences between heavy and light users when considering self-reported use, thus all hypotheses were rejected. However, the examination of the results indicated differences regarding perceptions of being heavy or light users. The more people perceive themselves as heavy users, the more diverse they perceive their content to be, the more they appreciate algorithmic recommendations, and the more satisfied they are with Discover Weekly.

KEYWORDS: *Discover Weekly, Spotify, Music Diversity, Algorithms Appreciation, Algorithmic Satisfaction,*

Table of Contents

Chapter 1. Introduction

With the development of music streaming services, new possibilities to listen and discover music have arisen. These days, users can constantly stream content without the need to pay for each item separately, as it was in the case of physical albums. Now, subscriptions to the music platforms provide customers with access to almost endless catalogues of audio files (Morris & Powers, 2015). The variety of content available to the users on those services shifted the manner, in which people consume new music items. Accordingly, to Morris and Powers “streaming services have also eagerly promoted a vision of the future where streaming provides a totalizing ‘musical atmosphere’ to satisfy any musical need at any moment” (2015, p. 109). In contrast as Kunaver and Požrl (2017) stated, access to such a broad offer of music might be problematic to manage for the users. They may find difficulties in discovering interesting pieces in a short time, which makes the process of listening to music more complicated. Therefore, music streaming platforms constantly develop their services to make them more tailored to the customers' needs and to make exploring music easier.

Music platforms provide their users with interactive tools, for instance, to create playlists and share them with the world, or to follow already created compilations of songs to discover new content. Kamehkhosh, Jannach and Bonnin (2018) argued that while consumers use these tools to expand their music libraries, it is still time-consuming and quite complicated to discover new music due to the amount of available content. Thus, a common practise by music services is to implement recommender systems. The recommender systems are known as the tools that select and suggest content to the users (Ricci, Rokach & Shapira, 2010). Their form can vary depending on the needs of the service, however, most of them focus on increasing sales and providing a diversity of items by understanding the customers’ needs. Thus, the recommender systems use gathered data about users and their preferences towards e.g. products or services and use them to select the most suitable offer for the consumers (Ricci et al., 2010).

The customers, on the other hand, are distinguished by a few characteristics that influence their music listening. Aspects like the subscription model, the quantity of music consumed daily or methods to discover the music, shape the way in which people are exploring diverse content. With the premium subscription, users are allowed to explore music catalogues without any limitations. Freemium users, however, receive music with a lower quality of sound and are interrupted with advertisements during the listening (Aguiar, 2017;

Waelbroeck, 2013). In addition, overall Internet usage has an impact on music exploration and listening. Thus, the quantity of time spent on listening to Spotify might have an influence on discovering new content and overall music diversity (Tepper & Hargittai, 2009). Therefore, by analysing the differences between particular groups of users might be relevant as they differ in music exploration and might perceive the diversity of their content differently.

The online platforms expand their algorithms and recommender systems to provide users with the most suitable and tailored content for them. Moreover, these algorithmically created recommendations have a significant prospective to facilitate discovering of new content that users of the platform are not familiar with (Hosanagar, Fleder, Lee, & Buja, 2013). Thus, this phenomenon brought many different opinions regarding the diversity of content recommended by algorithms. Scholars argue that recommender systems close people in ‘echo chambers’, where they receive similar content that matches their preferences, or that they obtain algorithmically created suggestions that they will likely agree with, known as the ‘filter bubbles’ (Möller, Trilling, Helberger, & van Es, 2018; Flaxman, Goel, & Rao, 2016). On the other hand, researchers argue that tailored recommendations positively impact diversity, as the algorithms present users with new content (Hosanagar, et al., 2013). Thus, by exploring whether algorithmically created recommendations increase or decrease the diversity of content might indicate interesting outcomes as they directly impact streaming service users.

In recent years, music streaming services replaced other channels of music distribution (Kim, Nam & Ryu, 2017), and shifted how people approach and listen to music. One of the most popular music streaming services is Spotify, which according to Statista (2020a), had 248 million monthly active users, marked by the end of the third quarter of 2019. Consequently, this placed Spotify on the top of the music streaming platforms in the world (De Silva, 2019). Moreover, this music service is using algorithms that recommend personalized playlists to their consumers. Every Monday, users of Spotify are introduced to 30 new songs from the *Discover Weekly* playlist, which is composed of the recommendation algorithms. Hence, by researching the connection between choices that algorithms made and how people encounter them, might bring relevant insights regarding the diversity of music and approaches toward algorithmic playlist.

Thus, this research will explore and provide insight into the music industry, artists and consumers of streaming services. The data gathered might contribute to the music industry by examining whether their recommendation systems work in line with their predictions. Likewise, this research may highlight the issues that can be fixed to improve the recommendation playlists, offered by streaming services as it will also measure satisfaction. The study will bring insights regarding users' preferences that Spotify can directly use to improve their *Discover Weekly* playlist. Additionally, society will become more aware of the issue regarding the diversity of content that algorithms recommend. Furthermore, this study will expose whether the algorithms are perceived to increase the diversity of music and whether people are satisfied with the recommendations they receive. Thus, it will highlight the potential negative aspects e.g. that algorithms steer users' preferences toward music and offer them similar content which lacks diversity. Therefore, this study will expose how users perceive *Discover Weekly* recommendations and whether these are accurate in matching listeners needs and music taste.

Moreover, as Ricci et al., (2010) state, recommender systems and algorithms became a popular topic of research. One of the reasons for that is the development of online sites e.g. Netflix, Amazon or Spotify, which are using them to make more personalized content for the users. Nonetheless, there is a research gap when it comes to discovering music with the use of recommended playlists. There have been several studies that focus on music recommendation systems and their influence on society (Slaney & White, 2006; Schedl & Hauger, 2015; Tang & Yang, 2017). In addition, scholars tend to focus on Spotify as the business model (Fleischer & Snickars, 2017; Kreitz & Nimela, 2010), or the music streaming services in general (Arditi, 2017; Wlömert & Papies, 2016). However, it seems that there are no insights on the playlists created by algorithms and the impact they may have on music diversity. Therefore, this thesis will contribute to the research field as it focuses on Spotify and their *Discover Weekly*. Furthermore, this playlist became one of the most popular tools for music discovery created by Spotify. Since 2015, when the playlist was officially launched, over 40 million of listeners started to use music recommendations created by algorithms (Prey, 2019). Consequently, this algorithmically created playlist became a new method to receive tailored suggestions that match users' needs and preferences. Hence, the analysis of the users of Discover Weekly playlist will allow bringing new information regarding the diversity of the content that is provided to them by algorithms. Besides, this thesis will explore how listeners of *Discover Weekly* perceive algorithms as recommendation tools and the extent to which they are satisfied with the algorithmically created playlist. Therefore, the main aim of this research is to answer the following question: *to what extent does the diversity of the music recommended by the Discover Weekly playlists differ between heavy and light users of Spotify?*

This thesis was organized to firstly introduce the main aim of the research and to briefly touch upon ideas that are building the research. In the second chapter, the literature and theories from other researchers are reviewed and used as building blocks to state hypotheses. The following chapter is focused on the research design and how the data gathering and analysis were guided. Moreover, the description of sample and data reduction is included in the methodology. The fourth chapter is a result section, where the outcomes of statistical analyses are presented. The last chapter includes the discussion on the insights that were analysed in the result section. In addition, this section contains the main conclusions and reflections on the study. At the end of the chapter, the limitations and guidelines for future researchers interested in this field are stated.

Chapter 2. Theoretical Framework

This chapter examines the existing theories regarding music streaming services and the impact of recommendation systems on users. As the music platforms constantly increase in popularity, they became an interesting object to study. The first part of this chapter highlights the developments of music streaming services and the music industry. In addition, this section underlines how people make use of streaming services and how they discover new music with the use of recommendation systems. The following fragment focuses on the streaming service – Spotify, and its users. Moreover, the distinction between heavy and light users is proposed, as the differences between them influence the way in which they discover new content and the extent to which it is diverse. The theories in the third part touch upon concepts related to recommendation systems and how they impact users. As the information that people are receiving by algorithms might not be diverse, the concepts of echo chambers and filter bubbles are defined. The next section sheds light on the perceptions that users of Spotify may have regarding the content provided by recommendation systems. As consumers might mistrust the algorithmic suggestions, the aversion towards them is established. In contrary, if consumers trust and believe that recommendations created by the systems are precise, the phenomenon of algorithmic appreciation occurs. At the end, the concept of satisfaction is underlined. This concept indicates the basic achievement of algorithms if the user is satisfied with its newly created playlist. These theories and concepts are backbones for the study, as each of them influences the music discovering and content diversity proposed to users of Spotify.

2.1. The music streaming services

Before trying to understand what role algorithms play in the music listening and what are the differences between the users of the streaming platform, it is necessary to understand the streaming music industry itself. Thus, this part highlights some insights regarding the streaming music market and how it developed with the expansion of technologies. Moreover, it explores the approaches that help users to discover new music and how music is consumed by them.

Many transformations and constant developments of the music industry were caused by the quick expansion of the Internet and new technologies (Kim, et al., 2017). As researchers argued, previously the artists distributed their music through tangible forms e.g. CD albums or cassettes (Kjus, 2016), and further through online downloads from the web

(Kim et al., 2017). According to Kjus (2016), the 2000s brought a new wave of music distribution: online streaming services, which shifted the way how people consume and discover music. The rise of these platforms was also caused by the developments of mobile devices, which influenced the accessibility to music (Kim, et al., 2017). Every year the number of new records released is growing due to the technological improvements. This reflects the claim by McCourt and Zuberi (2016) that the music content took upon a fluid form and became less tangible, which facilitated streaming services to continuously increase in popularity, leaving behind CDs and online-downloading methods (Trefzger, Rose, Baccarella, & Voigt, 2015). Moreover, as Waelbroeck (2013) argued, digital technologies shaped the way in which consumers discover new music and artists. In the past, music listeners had to purchase and collect separate cassettes or discs to listen to the audio content. Thus, it made music discovering more expensive and less accessible. The improvement of online media, social platforms, cloud computing and streaming services exposed users to large catalogues of music. In addition, these online tools facilitated the exploration and discovery of new music content and allowed users to receive tailored recommendations directly from the service. Waelbroeck (2013) claimed that this creates the phenomenon known as the ‘long tail’, as it generates business models grounded on less popular products, which would be difficult to find in regular shops. This corresponds to the claim of Tepper and Hargittai that “information technologies offer tools for users to navigate ever-expanding cultural catalogues” (2009, p. 232). Consequently, the accessibility to these wide catalogues encourages users to discover and experience new music. As scholars argued, these digital technologies decreased the costs of search for novel artists and downloading new songs, additionally, they allowed users to *try* the content before the purchase (McCourt & Zuberi, 2016).

As Thomsen (2013) claimed, “the underlying concept of streaming services relies on inducing music consumers to listen to streaming music on demand” (2013, p. 81). Wlömert and Papies (2016), stated that music streaming services are differentiated by the business models they adopt. According to scholars, the most popular is on-demand streaming, used by platforms like Spotify (Wlömert & Papies, 2016; Thomsen, 2013). This model allows users to access broad catalogues of songs, without paying for each item separately. It gives the customers two options of streaming subscription: monthly-paid and advertisements-based models. The first form of subscription, also called premium, charges consumers at a fixed rate each month and it offers additional benefits to the users. As Thomsen (2013) claimed, the paid subscription does not limit the access to the broad catalogues of music service, and it gives users an option to listen to the music offline through the application. On the other hand, the advertisement-based model allows for the free of charge access by getting income from advertising (Wlömert & Papies, 2016). However, the freemium model of subscription has its limitations. This subscription does not allow to access the music catalogues in the same sound quality as a premium subscription and has lesser access to music libraries (Waelbroeck, 2013). Therefore, the differences between subscriptions might contribute to answer the main research question as the freemium users might perceive diversity of music differently than premium users.

2.1.2. Discovering new music

As previously mentioned, the phenomenon of discovering new music is significantly impacted by digital platforms, as they allow users to access a large variety of content. Moreover, these services facilitated the rise of many online communities, where people can effortlessly discover new content and receive recommendations from others. As Waelbroeck claimed, these Internet-based communities created the phenomenon of the 'long tail', which is “a business model based on the exploitation of niche products hard to find in physical stores” (2013, p. 392). This exposure to the music available on on-demand platforms shaped the manner in which users discover new audio content. There are several approaches that consumers might take for music exploration. As Goldmann and Kreitz (2011) argued, there are two methods in which listeners can discover new music; searching, where users explore services to find songs or artists, and browsing, where consumers can display particular artist’s playlist. In contrary, McCourt and Zuberi (2016) claimed that nowadays music discovering is dependent on the online tools e.g. algorithmically created playlists, which direct users across the catalogues suggested to them based on their music preferences. In addition, Tepper and Hargittai (2009) argued that content discovering is based on the recommendations that people receive. They distinguish three methods in which consumers discover new music. Firstly, users base their discoveries on suggestions from friends and relatives. Secondly, they receive and acknowledge recommendations from the mainstream media, and thirdly from new media and algorithms (Tepper & Hargittai, 2009). Recently, scholars considered how consumers rely on recommendations from friends, social networks or algorithms. As Tepper and Hargittai (2009) suggested in their study, social media spread varied information, including news in culture from which people may receive novel content. While the scholars were researching students approaches towards recommendations and music discovering, they found that students acquire some suggestions from digital media, however, they find recommendations from their social groups and mainstream media more accurate (Tepper & Hargittai, 2009). In comparison, in later study Kjus (2016) highlighted that most of the time, music discovering is not initiated by the streaming platforms, but by the inspirations from acquaintances or live music concerts. Thus, even though there is a difference of seven years between these two studies, both highlight that people prefer recommendations from friends and traditional media. However, music platforms serve as great tools to expand music libraries by suggestions from peers (Kjus, 2016).

2.2. Users of Spotify

As mentioned in the introduction, there are 248 million active monthly users of Spotify, which makes it the leader among music streaming services (Spotify, 2020a). Every day, users access Spotify listen to their favourite music or to discover new content. Moreover, with the use of tools available on the service, listeners can organise their music into playlists, or search for already created compilations based on their preferences or mood (Goldmann & Kreitz, 2011).

Spotify offers two different subscription types for its users; freemium and premium version of subscription. Both models allow access to over 50 million songs and podcasts. However, the unpaid version interrupts listeners with the advertisements and a limited number of possibilities to skip to the next songs. On the other hand, Spotify premium works offline, ad-free and with unlimited chances to go throughout the broad catalogues of music (Spotify, 2020b). This reflects what Aguiar (2017) claimed influences the music listening, as the paid subscription allows for more active music discovering by the possibility of changing songs, and the free subscription which is a more passive way of music listening with the content restrictions (Aguiar, 2017). Consequently, as Mehrotra, Lalmas, Kenny, Lim-Meng and Hashemian (2019) argued, Spotify users can be categorised into active listeners and passive listeners. The distinction was made by the approach that consumers have towards music listening, in active listening people tend to discover and explore new music and artists more. Consequently, passive music listening was connotated with streaming music in the background or by accessing saved playlists. However, Schedl and Hauger (2015) defined three different users listening characteristics: diversity, mainstreamness and novelty. The diversity of music is based on the users' taste, measured by quantity of times the song is listened to and by the different genres appearing in the user's music compilations. Mainstreamness reflects the preferences toward popular songs and artists, and novelty is defined by the demand to discover new music. In addition, Aguiar (2017), claimed that users can be categorised by the quantity of time spent on music listening through the music platform. The quantity category reflects the amount of music that is consumed by the users and groups them into heavy or light users of streaming service, which was argued in more depth below.

2.2.1. Heavy Users & Light Users of Music Streaming Services

In the study regarding students and the methods in which they discover new music, Tepper and Hargittai (2009) claimed that heavy Internet users are expected to use new technology more to discover and consume new music content. And even though this study is from 2009, it is still assumed that heavy Internet users are spending more time on new technologies, which allow them to discover new content. Consequently, people who are less active in the web are considered light users, who do not discover the wide catalogues of music available online. On the other hand, Aguiar's (2017) study that focused on music streaming services argued that light users might be considered as people who consume less music through the service. In contrary, the heavy users are defined as listeners who consume a larger amount of music content that is available. In addition, Datta, Knox and Bronnenberg found that "streaming increases total consumption, leads to more variety, and facilitates the discovery of more highly valued music (2017, p. 19), which leads to the assumption that the more users are using music streaming services, the more diverse is their content. Furthermore, Prey (2017) claimed that, when users actively interact with the platform, they provide more detailed information regarding their preferences resulting in larger variety of content recommended to them by the algorithms. This approach goes in line with what Tepper and Hargittai (2009) found, that users who are actively discovering new music content will be expected to make use more of digital technology to do so.

Therefore, the main assumption is that heavy users are more exposed to diverse content as they use new technologies and algorithms to find new music more. Subsequently, light users spend less time on music listening and discovering, thus their content is less diverse. Hence, two hypotheses were stated to investigate whether different types of consumers make use of Spotify contrarily:

H1: *The heavy users of Spotify use the Discover Weekly playlist more than light users of Spotify.*

H2: *The heavy Spotify users have a more diverse Discover Weekly playlist than light Spotify users.*

2.3. The role of the Recommendation Systems

As the amount of data that circulates on the Internet is enormous, it created an issue for users to select the most relevant information (Bozdag, 2013). This situation led to creation of recommendation systems and algorithms by search tools like Google, social media like Facebook and streaming services like Spotify, which create tailored content that matches users' needs (Bozdag, 2013).

Recommendation systems can be defined as tools that propose content or products for consumers to make the process of decision-making easier. With a number of playlists overreaching 3 billion and 50 million songs, Spotify users are exposed to almost unlimited content (Spotify, 2019a). Consequently, consumers might feel overwhelmed by the amount of music available on the platform. Therefore, the music service provides users with a recommended playlist personalized for them. The *Discover Weekly* playlist is one of the examples that offer customers new content. From 2015, every Monday morning, users of Spotify are introduced to 30 new songs composed into one playlist (Prey, 2017). The playlist is personalized for each of the service subscribers separately, based on data gathered from their listening history (Spotify, 2019c). To elaborate more on how Discover Weekly is created, first it is important to analyse factors that build a personalized playlist, the algorithms of Spotify.

According to Prey (2017), Spotify is using a hybrid recommender system, which is a combination of specific models. Firstly, Spotify is using collaborative filtering, which gathers information about the music tracks and behaviour of users and their friends to make recommendations (Ciocca, 2017). The second model of recommendation algorithms used by the platform is Natural Language Processing. It focuses on text and lyrics of songs, and it searches for patterns related to the music (Boyd, 2019). The third category that improves the precision of Spotify recommendations is the raw audio model. This model is focused on highlighting the key audio elements of each song to further compare the new tracks with the songs that users enjoyed previously (Ciocca, 2017). As Thorat, Goudar and Barave (2015) claimed, it is expected that recommendation systems increase the diversity of content since they support the discovering of new items. Additionally, Ricci et al. (2010) stated that "in a recommendation list, it is more likely that the user will find a suitable item if there is a certain degree of diversity among the included items" (p. 26). However, as L'Huillier, Castagnos and Boyer (2015) noticed, recommendation systems do not take into consideration human factors i.e. context, confidence, explanation and need for diversity. These features play an important role during the decision-making process, especially regarding the need for diversity.

Moreover, they are also significant as they increase consumers' satisfaction (L'Huillier, et al., 2015). Hence, the algorithmically created *Discover Weekly* playlist is a tool to enhance content diversity and music discovering. Moreover, it enables users to expand their music catalogues from what they were already familiar with. Thus, the following hypothesis regarding differences between consumers content and recommended playlists is stated, assuming that algorithms offer more diverse music:

H3: *The heavy users of Spotify perceive Discover Weekly playlist to influence diversity of music more than light users of Spotify.*

2.3.1. The impact of personalized recommendations on users

The following section emphasises how personalized recommendations and algorithms might affect users. As the main focus of this paper is on the diversity of music content and how algorithms influence that, it is important to discuss concepts like echo chambers and filter bubbles, which are related to that variety (Möller, et al., 2018; Flaxman, et al., 2016; Bozdag, 2013).

As Bozdag (2013) emphasised, people actively contribute to the creation of online material, either by posting about themselves, their families or other aspects of their lives. Additionally, news and information are continuously produced by media outlets and other businesses (Bozdag, 2013). All of that creates an enormous quantity of data, which can be selected by the search engines, social media and recommendation systems and displayed to the users. As Bozdag (2013) noticed, this formed a new kind of gatekeepers, that are using recommendation systems and algorithms to choose content for its users. What Hosanagar, et al., (2013) stated is that recommendation systems and algorithms have a significant potential to facilitate consumers discovery and search of new content, which may be outside the range that they are familiar with. However, this brought many doubts raised by researchers that these algorithms influence negatively the content that users get by the lack of diversity within it (Möller, et al., 2018; Haim, Graefe, & Brosius, 2018; Helberger, Karppinen, & D'Acunto, 2018).

In the study made by Möller, et al. (2018), the researchers claimed that users are willingly closing themselves in 'echo chambers', when they are offered with sufficient choice. In addition, this phenomenon continues to present similar content, based on the persons' previous preferences and choices. Flaxman, et al. (2016), found in their experiment that participants select news articles that match their political values and beliefs. On the other hand, scholars argue that when people are inside the echo chambers, they will think that they received all of the information (Dubois & Blank, 2018). Further research led scholars to another concept, filter bubbles, that underlines the situation in which consumers are exposed to similar content. As Flaxman et al. pointed out, “search engines, news aggregators, and social networks are increasingly personalizing content through machine-learning models, potentially creating “filter bubbles” in which algorithms inadvertently amplify ideological segregation by automatically recommending content an individual is likely to agree with” (2016, p. 299). This can be also applied to music, as the algorithmically created recommendations might feed users with non-diverse content, based on their previous preferences. However, the scholars also argue that the increase of social media platforms and the Internet allowed people to access more diverse content and information. There are claims that in the music consumption the tailored recommendations expand the diversity of users’ playlists (Hosanagar, et al., 2013).

2.4. Perceptions of Algorithms for Music Discovery

As it was already stated, technological developments in the music industry and the streaming services brought many changes. Numerous companies, including Spotify, invested in recommendation systems, which would enrich searching and discovering new music. While scholars argue that algorithms can calculate data accurately and create propositions, which would match users’ preferences perfectly, there is a notion that recommendations from humans are still more precise (Yeomans, Shah, Mullainathan & Kleinberg, 2019). As Castelo, Bos and Lehmann (2019) suggest it is due to the fact that people can provide explanations to their suggestions and seem to be more confident, while providing information. Moreover, it is argued that recommendations from other humans include more subjective preferences and are based on the information about receivers. As Yeomans et al. (2019) state, people are searching for suggestions from close friends and family, as they know their tastes. In contrary, it is assumed that algorithms that build recommendation, work with limited data and insights regarding consumers unique preferences (Yeomans et al., 2019). These assumptions and predictions about algorithms and recommended content, built positive and negative perceptions regarding trust and satisfaction of suggested content.

2.4.1. Algorithmic Aversion and Appreciation

The purpose of algorithms is to provide consumers with new music content that is based on users' previous preferences and history of listening (Ziegler, McNee, Konstan & Lausen, 2005). However, there might be different approaches toward recommendation systems, reliance on them and their precision. When users do not believe in generic suggestions and do not accept the algorithmic judgement about their preferences, it is defined as algorithmic aversion (Logg, et al., 2018). On the other hand, the phenomenon to trust and prefer the suggestions made by algorithms is labelled as algorithmic appreciation. As there are many studies investigating an issue on whom users rely on more regarding content suggestions, there is a majority of studies showing that consumers prefer human recommendations over algorithms.

In the study by Castelo, et al. (2019), scholars revived theoretical frameworks conducted to measure trust in algorithms and their recommendations. Promberger and Baron (2006) and Longoni, Bonezzi, Morewedge (2019) focused their interests on the algorithms used in medical sphere. The outcomes indicated that people are averse towards medical algorithms, and that they prefer the doctor's opinion as they will take into consideration uniqueness of their conditions. In addition, researchers found that people tend to rate physicians more positively if they were not diagnosing them with the use of algorithms (Shaffer, Probst, Merkle, Arkes, & Medow, 2013). The mistrust towards algorithms was also underlined by Önkal, Goodwin, Thomson, Gönül, and Pollock (2009), who claimed that while forecasting the stock prices, humans did not appreciate algorithmic guidance. Another reason why people do not trust algorithms is because they do not provide explanations to their suggestions in comparison to human recommendations (Castelo, et al., 2019). Furthermore, Dietvorst, Simmons, and Massey (2014) argued that while algorithms were seen as better than humans at avoiding simple mistakes, people were perceived as more efficient in learning on mistakes and improving skills with time. Yeomans, et al. (2019) argued that people are averse towards algorithms, when it comes to predicting humour. Participants of the study claimed that they prefer to receive recommendations directly from other users or their friends. This phenomenon occurs due to the fact that people are not aware how the algorithms and recommendation systems work, for them the suggestions they get from other people are simpler to understand (Yeomans, et al., 2019). In regard to discovering new music, Tepper and Hargittai (2009) found that consumers still prefer recommendations received from their acquaintances and traditional media.

However, Logg, et al. (2019) suggested, people do rely on algorithms' recommendations. As the research participants indicated, they preferred advice given by the recommendation systems over the other people. They underlined algorithmic appreciation towards different advices, including business, art and music content and romantic interests. Scholars also found that study subjects preferred to select suggestions made by algorithms over the human judgments when they could choose. Moreover, researchers established that participants preferred algorithmic selections over their own choices (Logg, et al. 2019). As Castelo et al. stated, "algorithms become increasingly capable of outperforming humans at tasks ranging from making recommendations (for, e.g., music, movies, stocks) to diagnosing diseases and driving cars, a key issue is whether (or at least when or how quickly) and for what purposes humans will trust and use them" (2019, p. 13). The new positive shift towards algorithms can be seen in growing popularity of recommended playlists on Spotify. However, which users appreciate them or feel aversion to music created by algorithms might depend on usage of the service. As Tepper and Hargittai (2009) also pointed out, digital media are used to discover new music mainly by consumers who are heavy users. They do so to expand their music libraries by allowing technologies to search and recommend them new music content. Thus, the assumption was made, that heavy users will appreciate algorithmic suggestions more in comparison to light users, as they are less open for digital media to guidance their content. Therefore, the hypothesis was stated:

H4: *The heavy users appreciate the recommendations of Discover Weekly more than light Spotify users.*

2.4.2. Algorithmic Satisfaction

The exposure to the large amount of content available on the Internet challenges people with the phenomenon of so-called *information overload* (Hijikata, Shimizu & Nishida, 2009). Thus, to find fitting content to users' needs, online retailers or content providers are making use of recommendation systems. However, people who receive these suggestions might not be satisfied with the content they acquired. As the broad definition of satisfaction covers an idea of emotional response to expectations fulfilment (Giese & Cote, 2000), the satisfaction is usually measured to test the products or services and their quality among users (Perkins, 1993).

As Garcia-Gathright, St. Thomas, Hosey, Nazari and Diaz claimed, "designing music information access systems requires understanding the diverse needs of users and their expectations of system performance. Such needs include mood-setting, social standing, or nostalgia" (2018, p. 55). Thus, the interactions between users and music streaming services are crucial for gathering data on which the recommendations are built on. The more insights about person are collected, the more precise and personal the recommendations might be, and consequently it can increase the satisfaction of suggestions. As Kompan and Bieliková (2013) stated, satisfaction of recommender systems reflects the actual emotional approach toward suggestions made by the algorithms. Additionally, the satisfaction depends on the quality and precision of the suggestions that are made for users. Thus, the manner in which recommendations are presented and systematized is a crucial aspect, which can increase users' satisfaction (Nanou, Lekakos & Fouskas, 2010). Moreover, scholars found that if the satisfaction of recommendations is higher, it will positively impact the overall success of the platform (Chun & Hahn, 2006), and also it will develop loyalty and engagement between the service and a consumer (Chan, Cheung, Shi & Lee, 2014).

Therefore, as the algorithms gather more data about the users throughout their music consumption, it can be assumed that the recommendations might be more precise. The precision of the suggested content might be understood as the factor, which will increase the satisfaction of consumers. However, listeners who are satisfied with their music recommendations more, might be also consumers, who use the platform and algorithmic playlists more often and are heavy listeners. Thus, the two hypotheses were stated, as it is important to test whether users who use Spotify and Discover weekly playlist are more satisfied with the content that is recommended to them. Moreover, the second hypothesis is based on the differences in satisfaction between premium and freemium users as they access the music platform differently:

H5: *The heavy users are more satisfied with the recommendations of Discover Weekly than light Spotify users.*

H6: *Users with premium subscription model are more satisfied with the recommendations of Discover Weekly than users of freemium subscription model.*

Chapter 3. Methodology

3.1. Choice of method

The main aim of this research is to answer the question regarding the diversity of the music that is recommended to Spotify listeners by the *Discover Weekly* playlist, and how it relates to differences between the users. Thus, to compare groups of users and their content diversity on the music streaming service, the most suitable method for this study is a quantitative one. As Neuman (2014) claimed, quantitative research aims to "precisely capture details of the empirical social world and express what we find in numbers" (p. 204). In contrary, qualitative methods were not suitable as they aim to understand the insightful meanings of social phenomenon by analysing the intuitive and explanatory reflections of the respondents or units of analysis, which would not allow to measure the extent to which users differ regarding their music diversity (Brennen, 2017). Furthermore, as the core assumptions about the differences between groups of listeners and their music diversity were grounded in previous theories regarding algorithms and recommendation systems, this research is of deductive nature. In quantitative studies, the deductive approach is very often entailed as it allows to establish hypotheses founded on theories, which are later tested by the statistical analyses (Bryman, 2012). Thus, executing the quantitative research allows to present the outcomes from different users and measure the diversity of the music that they consume with the use of numerical data. Besides, due to its numerical nature, quantitative methods enable the researcher to analyse the outcomes with the use of statistical tests (Babbie, 2017).

As this study focuses on listeners' perceptions of algorithms and music diversity, surveys were found to be the most adequate technique that allows gathering information about these issues from a significant set of population (Matthews & Ross, 2010; Babbie, 2017). As Fink stated, "survey is a system for collecting information from or about people to describe, compare, or explain their knowledge, attitudes, and behavior" (2011a, p. 2). This method allows the researcher to ask many questions simultaneously by the use of different variables. Doing so allows us to collect different data and test various hypotheses by conducting one survey (Neuman, 2014). An additional advantage of questionnaires over the other research methods is the fact that they collect insights directly from the participants of the study in a short period of time (Fink, 2011a).

Moreover, as the main focus is on the online music streaming platform and its users, the most suitable form of collecting data is an online survey. As Van Selem and Jankowski (2006) argued, online surveys are an appropriate technique particularly to gather information about the users of the Internet or online services. Thus, to measure diversity and perceptions towards *Discover Weekly* playlist an online questionnaire gathered information directly from the Spotify users. As scholars also underlined, the reason to use this method is due to the fact that it allows collecting insights from the respondents that have particular interests in the subject and are willing to answer the questions without costs of conducting the research (Van Selem & Jankowski, 2006).

There are certain advantages and disadvantages while conducting an online survey. Overall, the fact that it is inexpensive and can reach significant group of respondents is beneficial for the researcher and the purpose of this thesis. In addition, online surveys allowed for flexible design and use of specialistic software that facilitates collection of the data (Neuman, 2014). However, by using surveys it is more difficult to make causal claims than with the use of other methods e.g. experiments. Moreover, researchers also argued that surveys conducted via Web caused challenges to data privacy and verification, unequal access to use the Internet and problems while designing survey with multiple software. Thus, to overcome these issues and support the data collection, the online software Qualtrics was used to organize the questions of the surveys. Moreover, this program assisted with data collection and analysis of the feedback from a large number of respondents, which saved time and helped categorizing the outcomes (Qualtrics, 2020). Furthermore, the surveys that are conducted via the software are completely anonymous, thus the concern regarding the privacy of respondents was not an issue, and it was assured that data will not be used for other purposes than answering the research question stated in this master thesis.

3.2. Sampling

As Fink stated, “a good sample is a miniature version of the population of which it is a part” (2011b, p. 3) thus, as this study focuses on Spotify and its users, the sample of population has to be based on the respondents that make use of the music streaming service. The usage of Spotify is the main characteristic that served as guideline of the selection process of the sample, as these participants were able to contribute to the research. The surveys were available to everyone, however, if respondents were not subscribers to the music platform they were not taken into consideration in this study. To distinguish if participants use Spotify or not, a filter question was included at the beginning of the survey, which excluded people who do not use the music platform. Hence, it created a sampling frame of people who are subscribers and are listening to music on Spotify.

However, as it was underlined in the theory part, there are four possible groups of platform users. The first two groups were based on the subscription model; free and premium. Additionally, there were categories created based on quantity of music streamed by users, which divided listeners on heavy and light. Therefore, to compare these groups and to be able to measure their music diversity it was preferable for the research purpose to have balanced number of respondents between these listeners categories. Thus, the sample size for this research was set at minimum of 300 respondents, which for survey research allowed to generalize the outcomes and state suitable final conclusions. Moreover, this significant group of study participants permitted to state assumptions regarding different groups of Spotify users, which decreased chances of sampling error (Bryman, 2012).

3.2.1. Sampling Method

As it was argued by Van Selem and Jankowski (2006), when conducting online surveys the sampling method is already assumed to be non-probabilistic. To select the sample with the probability method for the purpose of this study, the researcher would have to have full access to the list of all of the Spotify consumers. However, because it was impossible to receive the complete list and conduct the random selection of all users the non-probabilistic method was used. This technique is defined by the lack of random selection from the population based on probability, thus not all of the people have the same chances to be picked for the research (Babbie, 2017). Accordingly, for this research, the non-probability method is the most adequate as it allows to approach many users of streaming service and as Van Selem and Jankowski underlined, “even though these [online] surveys are not representative for the total population of Internet users, non-probability samples can be valuable as they may be representative for a subgroup of the total population” (2006, p. 439).

As in this research units of analysis were Spotify subscribers, the purposive method was selected. This technique of sampling focuses on picking the respondents with the particular characteristics based on the researcher judgements (Babbie, 2017). Moreover, the purposive method allowed to investigate the research question in more depth, as it focuses on the particular cases that will the most effectively present the phenomenon (Matthews & Ross, 2010). As scholars advised, to conduct the online survey among potential respondents that have above-mentioned characteristics, the Internet environment can be helpful (Van Selem & Jankowski, 2006). The online based groups operate as the places where people with similar interests or hobbies exchange their opinions and thoughts regarding various issues. Thus, to approach certain users, the online surveys were distributed through Facebook e.g. *Spotify*

Promotion with almost twenty-nine thousand followers, and Reddit communities e.g. *Spotify* with over two-hundred thousand followers or *Audio Engineering* with one-hundred eighty thousand followers. These social media also enabled the direct contact with people who have an understanding of the platform and are subscribers of it. Besides, it allowed accessing large population of people who were online and were willing to fill in the surveys. Furthermore, the survey was uploaded on *Spotify Community* website, where people share their interests and knowledge about the platform and music. As Van Selem and Jankowski (2006) pointed out, these self-organized groups are valuable for the researcher as they permit the access to characteristic population, which is central to answer the research question. Moreover, by reaching to different groups on various social media allowed to distribute survey to significant number of respondents. Thus, it gathered insights from different types of Spotify users and reduced the sampling bias.

3.2.2. Sample

After the data was collected, the total number of respondents that were 18 years old or older and agreed to take part in this research by signing the consent form reached 342 respondents. As this study focuses on the insights from Spotify users, the question regarding music platform usage was a filter question. Consequently, if respondents selected that they are not using Spotify, they were automatically directed to the end of the survey and were not taken into consideration while analysing the data. However, the final sample without participants that are not using Spotify, was still equal to N=342 (100%).

The descriptive statistics showed that among respondents, 297 (86.8%) are using premium version of subscription and 44 (12.9%) of respondents are using the freemium model to access Spotify. Moreover, the statistics indicated that there were 205 (59.9%) male respondents, 125 (36.5%) female participants, 4 (1.2%) respondents that selected ‘other’, and 7 (2%), who chose to rather not say regarding gender. Furthermore, survey responses came from 45 different countries, however, the majority of them were from The United States 140 (40.9%), followed by The United Kingdom 31 (9.1%), Poland 21 (6.1%), Canada 20 (5.8%) and The Netherlands 19 (5.6%). Participants’ average age was 26.73 (SD=7.24), with the youngest participants of the age of 18, and the oldest who had 58 years old. From 337 participants that named their highest educational level they obtained; the highest frequency had bachelor’s degree in collage (4-years) reaching 123 (36%) of respondents, followed by some collage but not degree 74 (21.6%), and high school graduate 52 (15.2%) and Master’s degree 52 (15.2%).

3.3. Operationalisation

The following part is crucial in the quantitative study, as it links the theoretical concepts and changes them into measurable variables (Neuman, 2014). The theory in this study touched upon various definitions and thoughts, which in operationalization section are translated into empirical measures, that aimed to test if the hypotheses occurs within the society (Neuman, 2014). Thus, in total there have been different variables selected that will facilitate to answer the research question regarding users of Spotify and the impact that algorithms have on music diversity.

To provide the anonymity of respondents, the consent form was added at the beginning of survey with the general introduction of the study. The participants were assured that the information they provide will be secured and not shared for other purposes than this master thesis. Following this part, the first question of the questionnaire filtered users of Spotify by asking directly whether respondents make use of music platform or not. When the answer was selected as 'no', they were automatically moved to the end of the survey. However, if the answer was chosen as 'yes', they were able to proceed with more questions.

3.3.1. Users of Spotify as the Independent variable

In this study, the independent variables are the heavy and light users of the music platform. In the survey, the part of the questions was dedicated to defining to which groups respondents belong to.

Heavy and Light Users of Spotify

To determine whether the respondents belong to the group of heavy or light listeners of Spotify, the survey has to examine question regarding quantity of music streamed and perceptions of being a heavy or light listener. As it was stated in the theory, the more users are consuming music on the platform, the most probable it is that they belong to heavy group of listeners. In contrary, if participants argue that they have a profile on Spotify, but do not necessarily use it, it might be stated that they belong to the group of light listeners. Hence, the question regarding amount of time spent on Spotify was an indicator of whether someone is light or heavy user of the music platform. Thus, the question asked respondents to indicate *"how many hours per week to you listen to Spotify, on average?".* As for the answer, the participants were asked to fill in he estimated time that they believe is an average of hours spent on listening to the music on Spotify per week. The distinction whether someone belongs to heavy or light group of users of Spotify was based on the report that indicated that on average people listen to music 18 hours per week (IFPI, 2019). Thus, when respondents indicated that they listen to Spotify on average less than 18 hours weekly they were considered as light users. In contrary, when participants stated that they listen more than 18 hours per week, they were assigned to heavy users' group. Additionally, to remove outliers, the maximum of 12 hours per day was set. Therefore, when respondents claimed they listen to more than 84 hours of Spotify weekly, they were not taken into consideration.

Moreover, four questions in the survey examined whether participants of the research identify themselves as heavy or light users of Spotify. Thus, the questions regarding their perceptions of affiliation were asked directly. Perhaps, *"do you agree or disagree with the statement: I consider myself as a light user of Spotify".* These questions were created with the use of Likert scale, where participants could choose from the scale of seven-point answers (1 = strongly disagree … 7 = strongly agree). In addition, six statements were added to distinguish passive or active use of Spotify. These statements were built on framework from Mehrotra, et al. (2019), where respondents could disagree or agree with the use of seven-point Likers scale. This part included statements e.g. *"I use Spotify to play music in the background"* or *"I use Spotify to explore artists or albums more deeply".* Thus, first three out of six statements were focused to select a passive use of Spotify, and accordingly next three statements were built in a manner to distinguish active use of music platform. Consequently, the reliability test was conducted whether these items can be combined into variables indicating passive or active music listening. The test exposed that for passive music listening Cronbach's $\alpha = .68$, and for active music listening the listening Cronbach's $\alpha = .71$, which mean that both variables are acceptable.

Freemium Subscribers & Premium Subscribers

As it was argued in the theory part, heavy users spend more time to discover new content, however, much also depends on the subscription model they have. As premium subscribers are not interrupted by advertisements, they are also allowed to select and play any audio they want, without an Internet connection. Therefore, the question regarding Spotify subscription model was included in the survey. This allowed to examine if the users with paid subscription have more diverse playlists as they have better access to music catalogues.

3.3.2. Dependent Variables

In this research there are several dependent variables that are influenced by the type of the Spotify user. As this study aimed to answer the research question to what extent does the diversity of recommended playlist differ between users, the variables as music diversity was stated. Moreover, as the *Discover Weekly* playlist was created by the algorithms, the different perceptions of them, including appreciation, aversion and satisfaction, were also the dependent variables in this research.

Moreover, in order to answer the research question and hypotheses, the first step was to organize gathered data and create new variables. As the measurements were based on previous research, reliability tests had to be conducted to measure whether they are still applicable. As Pallant (2007) claimed, reliability tests allow to find out whether the survey items measure the same concepts as intended. Moreover, the Cronbach's alpha coefficient was selected as the most commonly used indicator to test reliability of scales. In this analysis, when the Cronbach alpha is higher than .70, it means that scale is reliable. Thus, these tests were conducted for dependent variables.

Music Diversity of Discover Weekly

As Castells, Hurley and Vargas claimed, "diversity generally applies to a set of items or "pieces", and has to do with how different the items or pieces are with respect to each other" (2015, p. 884). As the surveys were sent directly to Spotify users, they were asked to answer Likert scale questions regarding diversity of their music content provided by *Discover Weekly*, with seven-point scale answers vary from strongly disagree to strongly agree. The questions that explored the overall perceptions of audio content provided by algorithms were stated based on the measurements used in the study by Tintarev, Lofi and Liem (2017). Firstly, the survey questioned respondents to indicate whether their *"Music provided by Discover Weekly playlist consist of a good variety of songs"* and the same sort of question was asked regarding the genres of music and artists recommended by the algorithms. Furthermore, participants were requested to state if the music suggested by *Discover Weekly* sounds similar to the music that they are already acquainted with and if the artists suggested by Spotify are often the same as the artists that they listen to e.g. "*Do you agree or disagree with the statement: I am often familiar with the songs that are suggested to me by Discover Weekly"*. Answers to these questions were grounded in the seven-point Likert scale varying from strongly disagree to strongly agree.

In order to organize and check whether there are subscales within diversity, the factor analysis was conducted. The first step was to reverse all of the statements with negative wording. There were three statements where the scores had to be reversed (where 1=7… 7=1) and the structure of statement was modified for the further analysis. The reversed statements were as follow: '*Discover Weekly provides me with music content that I do not recognize', 'Discover Weekly provides me with artists that I do not recognize',* and *'the artists I see on Discover Weekly and my music on Spotify are different'.* This procedure was done to allow for the factor analysis of the data regarding music diversity.

The 13 items which were based on the Likert-scale, were included in the factor analysis with the use of principal components with Varimax rotation based on Eigenvalues (>1), *KMO*=.86, X^2(*N*=210, 78) = 1210.12, $p < .001$. The resultant model explained 64.8% of the variance in perceptions of diversity of music provided by the *Discover Weekly* playlist. Factor loadings of individual items onto the three factors are present in the Table 1. The factors that were found are as follows:

Artists and Songs Diversity (*M*= 5.43, *SD*= .96): This factor includes four items that are related to the variety of artists and songs that are recommended by *Discover Weekly* playlist. This factor was combined of the perceptions like; "*Discover Weekly* consists a good variety of songs", "*Discover Weekly* consists a good variety of artists", and perceptions that "*Discover Weekly* playlist allows to discover new artists" and "*Discover Weekly* playlist allows to discover new songs".

Discover Weekly Content Familiarity (*M*= 3.62, *SD*= 1.04): The second factor was built based on five items related to familiarity with the content that is provided by *Discover Weekly.* It was based on statements regarding perceptions as follow; "I am often familiar with songs recommended by *Discover Weekly*", "I am often familiar with artist recommended by *Discover Weekly*", "*Discover Weekly* provides me with music content that I do recognize", "*Discover Weekly* provides me with artists that I do recognize" and "the artists I see on Discover Weekly and my music on Spotify are similar".

Genres Diversity (*M*= 4.30, *SD*= 1.17): The last factor was based on four items that are related to statements about diversity of music genres. This set of items included statements like; "content that is recommended by *Discover Weekly* allows me to explore new music genres", "I think that *Discover Weekly* provides me with diverse content", "I see a variety of music genres between my music on Spotify and *Discover Weekly* recommendations", "music provided by *Discover Weekly* consists of a good variety of music genres".

Table. 1. Factor and reliability analyses for scales for perceptions of diversity of music provided by *Discover Weekly* (N=207)

Items	Artists and Songs Diversity	Discover Weekly Content Familiarity	Genres Diversity
Music provided by Discover Weekly consists of a good variety of songs	.743	-	-
Content that is recommended by Discover Weekly allows me to discover new songs	.836	-	-
Music provided by Discover Weekly consists of a good variety of artists	.790	-	-
Content that is recommended by Discover Weekly allows me to explore new music artists	.741	-	-
I am often familiar with the songs that are suggested to me by Discover Weekly	-	.790	-
Discover Weekly provides me with music content that I do not recognize (R)	-	.611	-
I am often familiar with the artists that are suggested to me by Discover Weekly	-	.859	-
Discover Weekly provides me with artists that I do not recognize (R)	-	.636	-

The artists I see on Discover Weekly and my music on Spotify are different (R)	-	.588	-
Content that is recommended by Discover Weekly allows me to explore new music genres	-	-	.695
I think that Discover Weekly provides me with diverse content	-	-	.668
I see a variety of music genres between my music on Spotify and Discover Weekly recommendations	-	-	.769
Music provided by Discover Weekly consists of a good variety of music genres	-	-	.773
R^2	.23	.21	.20
Cronbach's α	.85	.80	.79

After creating three new variables the reliability test for them was conducted to analyse whether they can be combined into one variable that would indicate the overall music diversity. The test presented Cronbach's α = -.32 for these 3 items. Thus, the one variable could not be created. However, the two new variables indicating diversity of artists/songs and diversity of genres reached the Cronbach's α = .72, meaning it is acceptable, thus, these two variables were combined into one that was labelled indicating content diversity (*M*= 4.82, *SD*= .95).

Algorithmic Appreciation and Algorithmic Aversion

This variable was measured by questions regarding trust and preferences towards recommendations. Hence, a Likert scale was used to facilitate respondents' answers. As it was mentioned in the theory section, people tend to base their judgment on other people, and consequently they do not trust in algorithmic suggestions. Thus, the questions regarding trust were asked to assess to what extent Spotify listeners believe that algorithms know their preferences towards music. To measure whether respondents appreciate or not the algorithmically created playlists, three blocks of statements were built. The first two sections were asking participants about their perceptions toward *Discover Weekly,* with the use of seven-point Likert scale varying from strongly disagree to strongly agree. Firstly, respondents were asked about which recommendation matches their music tastes better i.e. *"songs recommended to me by my friends and family usually match my music taste".* The following section focused more on preferences on suggestions to search for new music i.e. "*having algorithmic recommendations from Discover Weekly playlists is a good way to find new music".* The third block of statements were considering whether participants agree or disagree. These statements were answered by the seven-point Likert scale, and they were asking respondents directly if they appreciate recommendations from algorithms. For instance, the statement *"I appreciate the recommendations provided to me by Spotify in Discover Weekly playlist"*. All of these statements were based on the framework from Thurman, Moeller, Helberger and Trilling (2019), however for the purpose of acquiring more information additional statements were created by the researcher in a similar manner, i.e. *"songs recommended to me by Spotify usually match my music taste"*.

The first step to begin the factor analysis was to change the negative wording of statements for the purpose of conducting the test. In the set of questions regarding the algorithmic appreciation and aversion, there was one statement *"I do not believe that algorithms can provide me with music that is fitting my preferences"* that was reversed. The values assigned were reversed, meaning that, for instance, 1=strongly disagree, now has a value of 7.

The 9 items which were based on the Likert-scale, were included in the factor analysis with the use of principal components with Varimax rotation based on Eigenvalues (>1), KMO=.72, $X^2(N=210, 36) = 1000.24$, $p < .001$. The resultant model explained 67.0% of the variance in preferences toward recommendations. Factor loadings of individual items onto the three factors are present in the Table 2. The factors that were found are:

Algorithmic Recommendations (M= 4.86, SD= 1.10): This factor was built on five items that are focused on algorithmic recommendations and respondents' opinions about them. For instance, statements included are; "songs recommended to me by Spotify usually match my music taste", "having algorithmic recommendations from Discover Weekly is a good way to find new music", or "I think that recommendations provided to me by algorithms on Spotify are predicting my music taste".

Media Recommendations (*M*= 3.92, *SD*= 1.32): This factor was constructed based on two items that indicate the extent to which people agree or disagree with statements regarding music recommendations from experts, media or journalists. The statements from this group are as follows; “songs recommended to me by media and music experts usually match my music taste” and “having songs recommended for me by editors and music journalists is a good way to find new music”.

Friends and Family Recommendations (*M*= 4.80, *SD*= 1.21): The last factor was combined of two items that are based on statements regarding recommendations from friends and family. These statements are; “having songs recommended for me by my friends is a good way to find new music” and “songs recommended to me by my friends and family usually match my music taste”.

Table. 2. Factor and reliability analyses for scales for algorithmic appreciation and aversion (*N*=341)

Items	Algorithmic Recommendations	Media Recommendations	Friends and Family Recommendations
Songs recommended to me by Spotify usually match my music taste	.825	-	-
Having algorithmic recommendations from Discover Weekly is a good way to find new music	.819	-	-
I appreciate the recommendations provided to me by Spotify in Discover Weekly playlist	.820	-	-
I think that recommendations provided to me by algorithms on Spotify are predicting my music taste	.743	-	-

I do not believe that algorithms can provide me with music that is fitting my preferences (R)	.540	-	-
Songs recommended to me by media and music experts usually match my music taste	-	.841	-
Having songs recommended for me by editors and music journalists is a good way to find new music	-	. 883	-
Having songs recommended for me by my friends is a good way to find new music	-	-	.864
Songs recommended to me by my friends and family usually match my music taste	-	-	.875
R^2	.32	.17	.17
Cronbach's α	.81	.71	.71

Algorithmic Satisfaction

The user satisfaction regarding the algorithms and the content that they provide, can be viewed as the overall usefulness and happiness of the suggestions (Mehrotra, et al., 2019). To measure satisfaction of algorithmically created *Discover Weekly* playlists, the frameworks from previous research were used to state survey questions. Firstly, respondents were asked about their overall satisfaction with Spotify. The next question regarding satisfaction of *Discover Weekly* was based on the framework from Garcia-Gathright, et al. (2018). It was constructed as follows: *"In general, how dissatisfied or satisfied are you with your experience using Discover Weekly?".* It was followed by three other questions regarding the usability of *Discover Weekly,* with the use of a five-point Likert scale. In addition, the statements regarding satisfaction were added to indicate the degree to which participants agree or disagree with them. This section was grounded on the measurements used by Bakalov et al. (2013). For instance, respondents were asked to indicate whether they agree or disagree with following statement *"most of the time I enjoy selection of music provided by Discover Weekly"*.

In order to organize and reduce the data, the questions regarding algorithmic satisfaction were divided into two sections. The first part included questions which directly asked participants about their Spotify satisfaction. The following section were focused on the *Discover Weekly* satisfaction.

In order to reduce and organize data, the first step was to analyse whether there is a relationship between overall Spotify satisfaction and *Discover Weekly* satisfaction. The relation between two variables was investigated using Persons correlation coefficient. The results indicated that there is a positive moderate correlation between Spotify and *Discover Weekly* satisfaction (r = .43, n = 210, p < .001). The following step was focused on the reliability of scales that measured how *Discover Weekly* predicts user's music tastes and preferences. The test indicated Cronbach's α = .82, which allowed to create new variable based on music taste and preferences predictions. Finally, the four statements regarding enjoyment of recommendations and whether they are a good fit to respondents' preferences were analysed with the use of factor analysis and reliability test. The two out of four statements had to be reversed i.e. *"Discover Weekly playlists are not enjoyable to me"* and *"the suggestions made by Discover Weekly do not match my music preferences"*. The factor analysis with these four items, which were based on the Likert-scale and were included in the factor analysis with the use of principal components with Varimax rotation based on Eigenvalues (>1), KMO=.80, X^2(N=210, 6) = 440.12, p < .001, showed one factor thus the statements were combined into one variable that indicated *Discover Weekly* Satisfaction. The resultant model explained 72.2% of the variance in satisfaction of *Discover Weekly*. The reliability test showed Cronbach's α = .88, and this variable was futured used to analyse the satisfaction of *Discover Weekly* playlist.

3.3.3. Additional variables

Additional variables were selected as they might impact the results of this research but also bring more insights regarding respondents. For this research, the additional variables are the demographic variables.

Demographic Variables

This category includes basic demographic questions that may influence or add more information to answer the research question. Therefore, participants were asked about their age, gender and nationality.

3.4. Validity and Reliability

Reliability assures that the data will be gathered consistently, and validity ensures that the measures focused on what was intended to be measured (Babbie, 2017). As Neuman (2014) claimed, reliability is the consistency of the outcomes when the research is conducted in identical conditions. Moreover, scholars emphasised that there are three types of reliability. Firstly, the stability reliability, which indicates that throughout the time the outcomes from the survey will not change. The second validity is the representative reliability, which as scholar claimed, “is reliability across subpopulations or different types of cases” (2014, p. 212). Thus, it is an indicator that different groups of respondents would answer in the same manner. The last type is the equivalence reliability, which is applied when there are multiple indicators. It measures the same concept in the same way, however with the different set of items, which was also involved in the process of creating the survey (Neuman, 2014). Therefore, for the purpose of the study, the reliability analysis was conducted with the use of SPSS. The reliability tests for variables indicated the Cronbach’s alpha above the minimum of 0.7, thus the measurements are acceptable and can be used in the analysis. For the variables regarding music diversity, the results of reliability tests were as follow; content diversity Cronbach’s $\alpha = .72$ and Discover Weekly content familiarity Cronbach’s $\alpha = .80$. For variables regarding algorithmic appreciation, the tests presented that algorithmic recommendations Cronbach’s $\alpha = .81$, media recommendations Cronbach’s $\alpha = .71$ and friends and family recommendations Cronbach’s $\alpha = .71$. Moreover, the reliability test showed that for variables regarding satisfaction the outcomes were as follow; Discover Weekly satisfaction = .88, and Discover Weekly predicts user’s music tastes and preferences Cronbach’s $\alpha = .82$,

On the other hand, validity reflects the authenticity of the measurements (Pallant, 2007). Thus, based on previous research and scales the concepts were guided on how to be measured. In addition, the sample reached over 300 respondents, which increased the validity of the research. Moreover, this size of the sample allows for better generalizations of the outcomes about the users of Spotify. However, as Prior (2009) argued when respondents are asked to estimate media consumption, they might not be precise, thus it has an impact on the gathered data about the number of hours respondents listen to music from Spotify. Moreover, the representativeness of the sample was affected by the respondents that were willingly filling in the survey, which could lead to self-selection bias. In addition, the scales to measure diversity, appreciation and satisfaction of recommended audio content, were taken and adapted from other scholars. As diversity is a complicated concept to measure with the use of a survey, the questions that examine overall satisfaction were based on the work from Tintarev, et al. (2017). To measure the preferences toward different types of recommendations, the framework from Thurman, et al. (2019) was selected to collect the most accurate information on users' perceptions of recommendations from algorithms, media or friend and family. As the satisfaction can be measured by its overall helpfulness and enjoyment of the recommendation (Mehrotra, et al., 2019), the several questions were stated to measure the overall satisfaction of Discover Weekly playlist. The majority of them were based on the framework from Garcia-Gathright, et al. (2018) and Bakalov et al. (2013). The questions built on the previously used frameworks increased the validity as it authorises the measurements.

Consequently, to enhance the requirements of reliability and validity a pilot version of the survey was pre-tested to assess how respondents understand and interpret questions and if they are clear to them (Neuman, 2014). Moreover, as Pallant stated, "a poorly planned and designed questionnaire will not give good data with which to address your research questions" (2007). Thus, the survey had to be pre-tested to understand if the structure is well created. As the pre-test indicated, there were some issues regarding repetition and understanding of statements. Thus, corrections were applied to make it more understandable and clearer for respondents. Moreover, an open-ended question where participants could give feedback was added.

Chapter 4. Results

4.1. Hypotheses Testing

4.1.1. Hypothesis 1

In order to test the first hypothesis: *the heavy users of Spotify use the Discover Weekly playlist more than light users of Spotify,* a chi-square test for independence was conducted as the most appropriate measurement to analyse the differences between heavy and light users of Spotify. For this measurement, the independent variable is the type of Spotify user and the dependent variable is the *Discover Weekly* usage. The chi-square test revealed that there are no significant differences between particular answers of *Discover Weekly* usage and heavy and light users of Spotify. The Chi-square test showed that type of users is not related to the *Discover Weekly* listening $X^2(N{=}326, 4) = 5.87$, p = .209. Therefore, the first hypothesis had to be rejected.

However, an additional analysis was conducted based on the perceptions of being heavy or light users of Spotify to study whether it might change the outcomes regarding music listening. To do so, the simple regression analysis was selected as it allows to explore the relationship between a dependent (continuous variable) and independent variable, based on the correlation (Pallant, 2007). For the purpose of running this statistical test, the perception of being heavy user of Spotify was selected as the independent variable, and the *Discover Weekly* listening as the dependent variable. However, to be more precise with the analysis, the values for a variable which measured quantity of times respondents listen to *Discover Weekly* were changed in regard to create continuous variable. Thus, when the answer to the question varied between 2-3 times a week and 4-6 times a week, the mean was used as an indicator. The new values were as follow: 0 = Never, 1 = Once a week, 2.5 = 2,5 times a week, 5 = 5 times a week and 7 = Daily. Linear regression with the quantity of time users listen to *Discover Weekly* playlist per week as criterion and the perception of being a heavy user of Spotify as a predictor was conducted. The model was found not to be significant, $F(1, 336) = 2.73$, $p = .100$, $R^2 = .01$. The perceptions of being a heavy user of Spotify has no significant influence on times respondents listen to *Discover Weekly* playlist ($\beta = .09$, $p = .100$).

4.1.2. Hypothesis 2 and Hypothesis 3

To begin the analysis of diversity of music provided by *Discover Weekly*, the first step was to elaborate on the responses regarding music diversity from the research participants. As the factor analysis indicated, there are two variables that are creating the diversity measurement; the overall content diversity and discover weekly content familiarity. The variable content diversity gathered data from N=207 of respondents where the mean of answers was M=4.82 SD=.95 and mode was equal to 5. These data indicate that majority of responses agreed to statements that *Discover Weekly* provides them with diverse content. On the other hand, the variable which presented the outcomes from the statements about being familiar with music and artists that are recommended by *Discover Weekly* showed that majority of N=206 respondents nor agree or disagree that algorithmically created playlist suggest them content that they did not know before (M=3.6, SD= 1.04, mode=4).

To test the second hypothesis: *the heavy Spotify users have a more diverse Discover Weekly playlist than light Spotify users,* the independent-sample t-test was conducted. As it was mentioned above, it will allow to compare heavy and light users of Spotify and their perception of music diversity. Thus, the independent variable was the type of Spotify user, and the dependent variable is the music diversity. These two variables were analysed separately with the use of independent-sample t-test.

The analysis indicated that the differences in diversity of content between heavy users heavy (M=4.88, SD=.95) and light users (M=4.76, SD=.95) are not significant $t(195) = -.88$, p=.919. Because $p > .05$, it indicates that heavy users do not have more diverse content of *Discover Weekly* than light users of Spotify. Moreover, the second test also showed no significant results $t(194) = 1.13$, p=.344. Thus, there are no significant differences regarding familiarity with *Discover Weekly* content between heavy (M=3.51, SD=1.07) and light users (M=3.68, SD=1.00). Because, for both of these tests, $p > .05$, it means that heavy users do not have more diverse content of *Discover Weekly* than light users of Spotify. As these two tests indicated p > .05, it means that H2 has to be rejected, meaning that the heavy Spotify users do not have a more diverse Discover Weekly playlist than light Spotify users.

As it was the case for the first hypothesis, the second was also analysed with the use of data regarding perceptions of being a heavy user of Spotify. For this reason, the multiple linear regression test was used to analyse whether respondents that see themselves as heavy users of music platform perceive the recommended content by *Discover Weekly* differently. A multiple regression analysis allowed analysing the relationship between the dependent variable, which is continuous, and several independent variables (Pallant, 2007). In this case, demographic variables were included as additional independent variables in this multiple analysis to explore whether they influence the diversity of content recommended by *Discover Weekly* playlist. The first step to conduct the analysis was to code the demographic variables as control variables with values 0 and 1. Thus, the variable gender was coded 0=male and 1=female, the other options i.e. ‘other’ or ‘rather not say’, were coded as missing. The education variable was also coded into a dummy variable, where 0 = did not complete higher education, and 1= completed higher education. In addition, the age variable was used in this multiple regression analysis.

The variable which measures content diversity was selected as the dependent variable, and the perceptions of being a heavy user of Spotify, education, gender and age were chosen as independent variables in this test. The multiple regression found to be significant, $F(4, 194) = 3.11$, $p= .016$, $R^2 = .06$. The outcomes presented that the perceptions of being a heavy user of Spotify has a positive significant influence on content diversity ($\beta= .20$, $p= .008$). However, the education ($\beta= -.08$, $p= .266$), gender ($\beta=.08$, $p= .268$) and age ($\beta=-.05$, $p= .518$) do not have significant influence on perceptions of content diversity of *Discover Weekly* playlist.

As the diversity of music was built on two variables, the same test was conducted to the variable regarding familiarity with the *Discover Weekly* content. The multiple regression analysis was conducted, where the dependent variable was the familiarity with the recommendations, and the independent variables were; the perception of a being heavy user of music service, education, gender and age. The multiple regression was found not to be significant, $F(4, 193) = 2.01$, $p= .094$, $R^2 = .04$. Thus, the perceptions of being a heavy user of Spotify do not have a significant influence on perceptions of familiarity with the recommendations from *Discover Weekly* ($\beta= -.07$, $p= .318$). Moreover, education ($\beta= -.06$, $p= .396$). and gender ($\beta=-.00$, $p= .975$) do not have a significant influence on perceptions of familiarity with the content that is suggested by *Discover Weekly* playlist. However, age ($\beta=.17$, $p=.031$) has a positive significant influence on familiarity with the content of *Discover Weekly*. Meaning, that the older users were, the more often they agreed they are familiar with the content recommended by the *Discover Weekly* playlist.

In order to analyse the third hypothesis: *the heavy users of Spotify perceive Discover Weekly playlist to influence diversity of music more than light users of Spotify*, a new variable had to be created based on the three items regarding perceptions that *Discover Weekly* provides diverse content. The Cronbach’s alpha for this variable reached .78, meaning the reliability was acceptable. The frequencies showed that out of $N=207$, the majority of respondents agreed that *Discover Weekly* provides them with new artists, new music genres and new songs. The independent-sample t-test for the new variable indicated that there are no significant differences between heavy (*M*=4.87, *SD*=1.05) and light (*M*=4.84, *SD*=1.08) users when it comes to perceptions that *Discover Weekly* influence diversity of music $t(195) = -.208$, $p = .440$, and because $p > .05$ the H3 has to be rejected, meaning that the heavy users of Spotify do not perceive Discover Weekly playlist to influence diversity of music more than light users of Spotify.

Furthermore, the variable regarding perceptions that *Discover Weekly* influence diversity of music was also analysed with the use of multiple regression analysis. A multiple regression with the impact of *Discover Weekly* as a criterion, and perceptions of being a heavy user of Spotify, education, age and gender as predictors was conducted. The model was found to be significant, $F(4, 194) = 2.59$, $p = .038$, $R^2 = .05$. The analysis presented that the perceptions of being a heavy user of Spotify has a positive significant influence on perceptions that *Discover Weekly* playlist influence the content diversity ($\beta = .18$, $p = .016$). Meaning that the more respondents perceive themselves as heavy users of Spotify, the more they perceive the *Discover Weekly* to influence the content diversity. However, the demographic variables indicated no influence on perceptions that *Discover Weekly* influence the content diversity, education ($\beta = -.12$, $p = .119$), gender ($\beta = .07$, $p = .312$) and age ($\beta = -.02$, $p = .834$).

4.1.3. Hypothesis 4

In order to test H4: *the heavy users appreciate the recommendations of Discover Weekly more than light Spotify users,* the factor *Algorithmic Recommendations* indicated the general agreement or disagreement that algorithms can predict music taste precisely. Moreover, the other two factors; *Media Recommendations* and *Family and Friends Recommendations* were also analysing if there are significant differences between heavy and light users. Thus, the three independent-sample t-tests were conducted to analyse whether heavy users appreciate recommendations form *discover Weekly* more than light users.

The first analysis revealed that heavy users (*M*= 4.92, *SD*= 1.17) and light users (*M*= 4.80, *SD*= 1.07) do not significantly differ in regard to algorithmic appreciation of recommendations $t(324) = -.10$, p=.309. Thus, the *p*-value is higher than .05, the H4 has to be rejected, meaning that heavy users do not appreciate the recommendations of Discover Weekly more than light Spotify users. The following analysis was based on preferences toward recommendations from media or journalists. The t-test indicated that heavy users (*M*=

4.01, *SD*= 1.38) differ in preferences to media recommendations than light users (*M*= 3.87, *SD*= 1.52), however it is not a significant difference *t*(324) = -.93, p=.375. Thus, there are no significant differences regarding preferences on recommendations from media or media experts between heavy and light users. Moreover, the third test was conducted to analyse whether there are differences regarding suggestions from friends and family between users. The analysis revealed that amongst heavy users (*M*= 4.74, *SD*= 1.20) and light users (*M*= 4.85, *SD*= 1.21) there are no significant differences *t*(324) = .85, *p* =.703.

However, in the survey there was one question which directly asked respondents if they agree or disagree with the following statement: *I appreciate the recommendations provided to me by Spotify in Discover Weekly playlist.* Therefore, to answer H4, data from this statement was analysed with the use of independent-sample t-test to measure if heavy users appreciate the *Discover Weekly* recommendations more than light users. The analysis revealed that, heavy users (*M*= 5.06, *SD*= 1.57) do not appreciate recommendations more *t*(324) =-1.05, *p*=.610, than light users (*M*= 4.89, *SD*= 1.43). Therefore, the H4 has to be rejected, meaning that the heavy users do not appreciate the recommendations of Discover Weekly more than light Spotify users.

Moreover, these three variables were analysed with the use of data regarding perceptions of being a heavy user of Spotify and demographic variables. The multiple regression was conducted to analyse whether respondents that see themselves as heavy users of music platform and with different demographics perceive the recommendations from algorithms, media or friends and family differently.

Firstly, the variable regarding algorithmic recommendations was selected as the dependent variable, and the perceptions of being a heavy user of Spotify, education, gender and age served as independent variables in this multiple regression analysis. The test was found not to be significant, *F*(4, 315) = 1.94, *p*= .104, R^2 = .02. However, the perceptions of being a heavy user of Spotify has a positive significant influence on appreciating algorithmic recommendations (β= .13, *p*= .023). Which means that the more participants perceive themselves to be heavy users, the more they appreciate the algorithmic recommendations. In contrary, education (β= .00, *p*= .947), gender (β= .03, *p*= .560) and age (β= -.05, *p*= .419) do not have influence on appreciating algorithmic recommendations.

The following multiple regression analysis was based on media recommendations variable, which was the dependent variable in this test, and the perception of being a heavy user of Spotify and the demographics as the independent variables. The results presented a significant outcomes *F*(4, 315) = 2.41, *p*= .049, R^2 = .03. The results indicated that the perception of being a heavy user of Spotify has a positive significant influence on appreciating the recommendations from media and journalists (β= .17, p= .004). Meaning that the more respondents perceive themselves as heavy Spotify users, the more they appreciate the recommendations from media and journalists. However, the education (β= -.01, p= .842), gender (β=.03, p= .547) and age (β=-.00, p= .944) do not have significant influence on appreciation on recommendations from media and journalists.

The third multiple regression analysis was conducted with the dependent variable as recommendations from friends and family, and the independent variables as the perceptions of being a heavy user of Spotify, education, gender and age. The test was found not to be significant, $F(4, 315) = .99$, p= .412, $R^2 = .01$. Meaning that the perceptions of being a heavy user of Spotify (β= .06, p= .324), education (β= .09, p= .134), gender (β= .02, p= .712) and age (β= .02, p= .804) do not influence the appreciation of recommendations from friends and family.

The variable that asked respondents directly whether they appreciate algorithmically created recommendations was also tested with the use of perceptions of being a heavy user of Spotify and demographic variables. The analysis indicated no significant results $F(4, 315) = 1.02$, p= .397, $R^2 = .01$. Thus, perceptions of being a heavy user of Spotify do not have a positive significant influence on the general appreciation of algorithmically created *Discover Weekly* playlist (β= .11, p= .057). Moreover, education (β= .00, p= .950), gender (β=-.02, p= .708) and age (β= -.00, p= .966) also do not influence overall appreciation of algorithmically created recommendations from *Discover Weekly* playlist.

4.1.4. Hypothesis 5

In regard to analyse the fifth hypothesis: *the heavy users are more satisfied with the recommendations of Discover Weekly than light Spotify users*, the means were compared with the use of independent-sample t-test. To accept or reject hypotheses two analyses were conducted. Firstly, the differences regarding satisfaction of *Discover Weekly* predictions about taste and preferences in music were tested between heavy and light users. Furthermore, the test compared differences between heavy and light users about the overall satisfaction of *Discover Weekly*.

The first test revealed that heavy users (M= 3.06, SD= .80) and light users (M= 3.13, SD= .77) do not differ in agreement or disagreement about satisfaction on recommendations that predict taste and music preferences $t(195) = .66$, p=.836. Because $p>.05$, it means that the hypothesis has to be rejected. Moreover, the second analysis of overall *Discover Weekly* satisfaction underlined that heavy users (*M*= 5.02, *SD*= .14) do not differ *t*(195) = .92, *p*=.437, than light users (*M*= 5.16, *SD*= 1.08). In both cases the *p*-value is higher than .05, thus the H5 has to be rejected, meaning that the heavy users are not more satisfied with the recommendations of Discover Weekly than light Spotify users.

For more detailed analysis of users' differences, the multiple regression was conducted with the independent variables as the perceptions of being a heavy user of Spotify and demographics. The first test included the satisfaction of predictions regarding taste and preferences in music provided by *Discover Weekly* as the dependent variable. The multiple regression revealed that test is not significant $F(4, 194) = .79$, $p= .533$, $R^2 = .02$. Thus, the perceptions of being a heavy user of Spotify (β= .10, *p*= .196), education, (β= -.09, *p*= .218), gender (β= .05, *p*= .468) and age (β= .04, *p*= .607) do not have a significant influence on satisfaction of predictions about taste and preferences in music provided by *Discover Weekly*.

The second multiple regression analysis was conducted with the use of overall satisfaction of *Discover Weekly* as the dependent variable and perceptions of being a heavy user of Spotify and demographics as independent variables. The test was found to be significant, $F(4, 194) = 3.25$, $p= .013$, $R^2 = .06$. The results exposed that education (β= -.22, *p*= .003) has a negative significant influence on the overall satisfaction of *Discover Weekly*, which means that people with higher education were less satisfied with the playlist. On the other hand, age has a positive significant influence on satisfaction of algorithmically created playlist (β= .17, *p*= .037), thus the older people were, the higher the satisfaction was with their algorithmically created playlist. However, perception of being a heavy user of Spotify (β= .06, *p*= .050) and gender (β= .11, *p*= .147) do not influence overall satisfaction of *Discover Weekly* playlist.

4.1.5. Hypothesis 6

The last hypothesis aims to analyse the differences between users with different subscription models; premium or freemium. As the statistical analysis indicated, from *N*=341 participants that answered the question about subscription type, only 44 (12.9%) stated that are using advertisement-based Spotify access. On the other hand, 297 (86.8%) claimed that they have paid accounts on the music platform. Thus, to test hypothesis stated: *users with a premium subscription model are more satisfied with the recommendations of Discover Weekly than users of a freemium subscription model,* an independent-sample t-test was conducted.

The statistical measures indicated that premium users (*M*= 5.11, *SD*= 1.10) do not differ significantly from freemium users (*M*= 4.85, *SD*= 1.10), when it comes to overall

Discover Weekly satisfaction $t(205) = -1.05$, p=.854. Since the $p > .05$, the hypothesis had to be rejected, meaning that users with a premium subscription model are not more satisfied with the recommendations of Discover Weekly than users of a freemium subscription model.

An additional measurement was conducted to examine whether there are differences between premium and freemium subscribers and perception of being a heavy user of Spotify. To do so, another independent-sample t-test was conducted. The dependent variable for this analysis was the subscription model and the independent was the perception of being a heavy user of Spotify. The test revealed significant results that premium users (M= 5.49, SD=2.06) perceive themselves as heavy users of Spotify more often than freemium users (M= 5.49, SD=2.06), $t(50.147) = -3.91$, $p < 0.001$.

Chapter 5. Discussion and Conclusions

This section is focused on answering the main research question of this master thesis and to present the central conclusions of the findings. Moreover, this chapter will elaborate on the results from the statistical analyses of the gathered information. Additionally, the limitations of the research will be presented as they are a fundamental reflection of the study. Lastly, this section will underline the recommendations for the future researchers that are interested in studying this or similar topic.

5.1. Discussion

The overall aim of this thesis was to highlight the differences between users of Spotify and their musical diversity. Moreover, this study examined insights regarding users' perceptions of algorithmically created recommendations and satisfaction of *Discover Weekly* playlist. The statistical analysis from data gathered through surveys, presented many interesting differences, even though they were contradicting assumptions stated in hypotheses and concepts from the theory section.

The insights regarding heavy and light users on listening to *Discover Weekly* playlist did not indicate any significant differences. Meaning that heavy users do not listen more to algorithmically created playlist than the light users. These outcomes are contradicting the assumption made by Tepper and Hargittai (2009) who claimed that heavy Internet consumers use new technological tools more to consume new content. However, this research was conducted in 2009, which might be considered as not the most relevant indicator, as the average time spent on Internet usage increased since then. In addition, the perceptions of being heavy or light users were analysed. The statistical test highlighted that there is no influence on listening to *Discover Weekly* and perceptions of being a heavy or light user of the music platform.

5.1.1. Music Diversity

As the focus of this thesis was to indicate the differences between heavy and light users and their diversity of *Discover Weekly*, the analysis of data presented that there are no differences between these two groups of listeners. Hence, the amount of time users spent on listening to music through the Spotify do not influence the diversity of recommended music, which is challenging claims made by Prey (2017) and Tepper and Hargittai (2009). Moreover, the music diversity was combined of two different items; the overall content diversity of *Discover Weekly* and perceptions of being familiar with content recommended by *Discover Weekly* playlist. The analysis for both factors showed that there are no significant differences between heavy and light users. Mutually, heavy and light users agreed that algorithmically created playlist provides them with diverse content and recommends them artists, songs and genres that they are not familiar with. These findings support the concept that algorithmically created recommendations increase the diversity of content as they facilitate the discovering of new music (Datta et al., 2017; Hosanagar, et al., 2013).

Additionally, the analysis of perceptions that *Discover Weekly* influences the diversity of content indicated that there are no differences between heavy and light users. Both groups of listeners indicated that the *Discover Weekly* is facilitating the music discovering. Thus, it can be argued that the algorithms are recommending content, which is unfamiliar to heavy and light users of Spotify. This refutes the concept that algorithms keep listeners in filter bubbles, where they are exposed only to similar content (Dubois & Blank, 2018).

However, when the perceptions of being a heavy user of Spotify and demographics were analysed, the outcomes revealed differences in music diversity of *Discover Weekly*. The potential implication for that could be caused by respondents who indicated to listen to Spotify less than 18 hours per week, however, they stated they consider themselves as heavy users of the platform. Moreover, as it was previously mentioned, when participants are asked to estimate media consumption, they might not be precise (Prior, 2009), which may influence the results. Nevertheless, the analysis indicated that the more respondents perceived themselves as heavy users of Spotify, the more diverse is their music content of the *Discover Weekly* playlist. However, when perceptions of being a heavy user of Spotify and being familiar with the algorithmic suggestions of *Discover Weekly* were analysed the results revealed no differences. Furthermore, the study revealed that when respondents perceive themselves more as heavy users, they perceive *Discover Weekly* to influence their music diversity more. These findings are again supporting claims that tailored recommendations created by algorithms increase the diversity of music offered to listeners of Spotify (Hosanagar, et al., 2013). On the other hand, the demographics of users presented that there are no differences between education, genders and age on perceiving the diversity of music recommended by the *Discover Weekly*. However, age was found to have a positive influence on being familiar with the recommendations offered by *Discover Weekly*. This means that the older the respondents were, the more often they agreed to be familiar with algorithmically created suggestions.

5.1.2. Algorithmic Appreciation

As the analysis indicated the perception of algorithmic recommendations is not impacted by the number of hours they spend on listening to the music on Spotify. There were no significant differences between heavy or light users regarding appreciating algorithmic recommendations from *Discover Weekly*. In general, respondents claimed that they trust and rely on the algorithmic recommendations of *Discover Weekly*. This outcome highlights the approach of algorithmic appreciation (Logg, et al., 2018). Furthermore, when respondents were asked directly whether they appreciate algorithmic recommendations, the results presented that participants agree that *Discover Weekly* often match their music preferences and tastes. However, there were no differences between heavy and light users. These outcomes reflect what Castelo et al. (2019) pointed out that algorithms are increasingly efficient in making recommendations regarding music that is matching listeners taste. Nevertheless, these results are contradicting what Yeomans et al. (2019) claimed that algorithmic recommendations are built on limited information of the user and thus, do not match consumers preferences.

In addition, when the perceptions of being a heavy user of Spotify were analysed the outcomes indicated differences between users. When respondents perceive themselves as heavy users of Spotify, they tend to appreciate the recommendations from *Discover Weekly* playlist more. Furthermore, the analysis of education, gender and age did not indicate any influence on appreciating algorithms. These outcomes indicated that overall users of Spotify are appreciating recommendations that *Discover Weekly* suggests.

As Tepper and Hargittai (2009) suggested, people tend to prefer recommendations from traditional media and their friends more, than from algorithms. However, the overall results presented lesser agreement on appreciating recommendations from media and journalists in comparison to algorithmic recommendations. The results from the statistical test indicated that there are no differences between heavy and light users of Spotify on appreciating the media recommendations. Nevertheless, the analysis of perceptions of being a heavy user indicated that the more respondents perceive themselves to be heavy users, the more they appreciate the recommendations from media and journalists. In addition, the education, gender and age do not influence the appreciation of media recommendations.

The outcomes from the analysis of recommendations from friends and family indicated overall appreciation towards them. The analysis did not present any differences between heavy and light users. Moreover, there is no influence on perception of being a heavy user of Spotify, or demographics on appreciating recommendations from acquaintances. The results reflect the assumption that users appreciate suggestions from friends and family, however, it is contradicting the notion that listeners prefer these recommendations over the algorithmic suggestions (Tepper & Hargittai, 2009).

5.1.3. Algorithmic Satisfaction

The statistical analyses of satisfaction of *Discover Weekly* exposed that there are no differences between heavy and light users. This is the case for both variables that measured satisfaction of algorithmically created playlist. Thus, the heavy users of Spotify are not satisfied more with predictions of their music taste and preferences, and overall satisfaction of *Discover Weekly* than light users. What is more, in general respondents indicated that they are satisfied with the recommendations provided by *Discover Weekly* playlist. Thus, the satisfaction of algorithmically created playlist does not depend on the quantity of hours users spent on listening to music on Spotify. However, the satisfaction of *Discover Weekly* is influenced by the precision of recommendations users receive (Garcia-Gathright, et al., 2018).

Furthermore, the perceptions of being a heavy user were analysed. The outcomes presented that perception of being a heavy or light user do not have any impact on the satisfaction of music provided by *Discover Weekly*. Moreover, the analysis of participants demographics; education, gender and age, indicated no differences when it comes to satisfaction of predictions of music taste and preferences. However, when the overall satisfaction of recommendations was analysed, the results revealed that there are differences between people who completed higher education, and those who did not. The outcomes exposed that people who obtained a higher educational degree are less satisfied with the music content provided by *Discover Weekly.* Moreover, age was found to influence the overall satisfaction of *Discover Weekly.* Hence, the older people were, the more satisfied they were with the algorithmically created playlist.

In addition, the analysis of different subscription models and how they impact the satisfaction of *Discover Weekly* was conducted. The results presented that there are no differences regarding satisfaction of recommendations from algorithmically created playlist between freemium and premium users. Thus, the fact that freemium subscribers are interrupted with advertisements and have lower sound quality do not impact the satisfaction of *Discover Weekly* (Waelbroeck, 2013). On the other hand, the subscription model has an impact on the perception of being a heavy or light user of Spotify. The analysis showed that premium users perceive themselves as heavy users of music platform more often than light users. Nevertheless, the outcomes might be impacted by the larger number of premium subscribers (N= 297) over freemium users (N=44) that took part in this research.

5.2. Conclusions

The main research question that was stated, asked *to what extent does the diversity of the music recommended by the Discover Weekly playlists differ between heavy and light users of Spotify*. In order to answer it, six hypotheses regarding differences between users were stated. The analysis of data indicated that there are no differences between heavy and light users of Spotify, when they are divided based on the quantity of time they listen to the music on the platform. Thus, all five hypotheses regarding heavy and light users had to be rejected. Therefore, the main assumptions that the more music is streamed over the platform, the more diverse and tailored the content is (Datta, et al., 2019) had to be rejected. Additionally, the sixth hypothesis that aimed to exposed differences between subscription models and overall satisfaction had to be rejected. Even though, the freemium subscription model limits the accessibility and quality of content that is streamed (Waelbroeck, 2013), there are no differences between premium and freemium users and their overall satisfaction of music provided by *Discover Weekly* and Spotify.

Even though the hypotheses had to be rejected and there are no significant differences between heavy and light users, this research exposed many additional insights, based on the perceptions of being a heavy or light user. For instance, the more respondents perceived themselves as heavy users of the music platform, the more diverse content they perceive to have. Additionally, people who see themselves as heavy listeners of Spotify tend to appreciate the algorithmically created *Discover Weekly* more. However, when it comes to the overall satisfaction of the algorithmically created playlist, there are no differences between users divided by the quantity of time, between users that perceive themselves as heavy or light, or between different subscription models.

Likewise, the gathered and analysed data exposed more general insights about users of Spotify and *Discover Weekly* playlist. Overall, respondents tend to perceive the recommended music content as diverse. These outcomes indicate that developed algorithms created by Spotify can precisely suggest novel and diverse content to its users. Additionally, there is a general agreement that algorithmically created *Discover Weekly* is a good way to receive music recommendations. Thus, people who are interested in expanding their music catalogues might use algorithmically created playlist for that purpose. Furthermore, the agreement on the overall satisfaction of Spotify and *Discover Weekly* was the case for the majority of respondents. This finding highlights the fact that algorithmically created playlist suggests listeners artists, genres and songs that match their music tastes and preferences.

Additionally, the research presented insights on respondents' overall preferences toward music recommendations. As Tepper and Hargittai (2009) emphasised, there are three main methods of receiving suggestions; from friends and family, mainstream media and new media and algorithms. While this study did not find any differences between particular groups of users, it highlighted the respondent's preferences on recommendations. As the survey exposed, people believe that recommendations from friends and family are a good fit their music taste and preferences. This reflects what Yeomans et al. (2019) stated, that people tend to search for recommendations from acquaintances as they know their music taste. In addition, respondents stated that algorithms have the ability to recommend music that they might be interested in. However, when they were asked regarding media preferences, the outcomes indicated lesser agreement that journalists and mainstream media can provide suggestions that fit their music preferences.

5.3. Limitations

While this research presented many important insights regarding music consumption and how it impacts the perceptions of recommendations and diversity, it also has several limitations. First of all, the majority of data was collected from users of the Reddit platform, where they are actively participating in online discussions. As Tepper and Hargittai (2009), highlighted heavy Internet users are expected to use online tools and new media more, and Reddit is one of these tools. Thus, users often are perceived as the heavy users of the Internet, which impacted the outcomes, as they typically where the heavy Spotify users as well. Moreover, the survey was distributed on the Reddit groups that focused on music listening or specifically on Spotify. Thus, the outcomes from these respondents might be more critical in comparison to people who are lighter users of Internet and Spotify.

In addition, the distinction between heavy and light users was based on the respondent's estimations, therefore the data about the quantity of time they listen to the music might not be considered as the most accurate measure. Likewise, the world pandemic of COVID-19 might also have an impact on the quantity of time people listen to music on Spotify. Because data was collected during the restrictions where the majority of people was forced to stay home, respondents might consume more music weekly than before the pandemic.

Furthermore, the disproportion of premium and freemium users could have limited this research. As the results presented, there are no differences between these two groups, however, the significantly smaller size of freemium users could be the reason for lack of variety. Additionally, because the distribution of the survey was based on social media like Reddit and Facebook, it could be a reason for the imbalances of the demographics. Firstly, the majority of respondents vary between 18 and 34 years old (N=298, 87.2%), it could also impact the results, as they are more actively interacting with online platforms like Spotify. Moreover, as stated before, the majority of respondents were from United States of America (140, 40.9%), where the second largest place of residence was United Kingdom (31, 9.1%). These disproportions might be considered as the sample bias, as it presents the majority of insights from respondents of particular country.

Even though this research reached the meaningful rate of respondents that are using Spotify (359), the number of participants that do not use *Discover Weekly* was quite large (134, 39.2%). Thus, these respondents were excluded from the part of the survey regarding the perceptions of music diversity of the algorithmically created playlist. This could impact the results of this study. Therefore, for future scholars it would be advisable to extend the sample and to gather data from more *Discover Weekly* users, which can impact the outcomes.

5.4. Future research

Overall, this research showed that more studies are needed to explore algorithmically created *Discover Weekly* playlists. As this study exposed, there were no major differences between heavy and light users based on the quantity of time. However, more research could be done to expose whether different factors i.e. active and passive usage, have more significant influence on music diversity of *Discover Weekly* playlist. In addition, for the future researchers it would be advisable to distinguish heavy and light users on more precise measurement than the estimation of the time.

Furthermore, this study focused on particular *Discover Weekly* playlist, where there are different algorithmic recommendation playlists suggested by Spotify. Thus, for future scholarship, the exploration of different playlists created by algorithms would be suitable to study. Moreover, this research could be expanded to different or all of the music streaming services. This research was based on Spotify and its users, however, nowadays there are multiple platforms that people use i.e. Apple Music or Deezer, that offer algorithmic recommendations. As Waelbroeck (2013) argued, the developments of technologies changed the way in which people listen and explore new music. Thus, the constantly changing streaming platforms are the grate phenomenon to analyse how they impact the society.

The following reflection on future research was based on the comments regarding the survey. As this study focused on perceptions that users of Spotify have on the music diversity and algorithms, it would be advisable to change the method of research to receive a more in-depth understanding of this phenomenon. Several respondents reflected on the overall usage of *Discover Weekly*. Thus, the qualitative method of research would be fascinating, because it might expose many interesting perceptions and insights on the music diversity and precisions of algorithmic recommendations. Additionally, by conducting interviews, respondents can bring extra information, which was impossible to collect with surveys.

Lastly, this research was built on previous theories and measurements and could be applied to different media content. Thus, future research could focus on perceptions of different entertainment media i.e. movies or TV series, to analyse whether algorithms expand people's libraries or if they keep them in filter bubbles. Moreover, more studies regarding filter bubbles or echo chambers would be needed, as those are the factors that influence the diversity of content. For instance, it would be also advisable to research whether algorithms allow discovering more niche artists and music genres. In addition, studying if the algorithms help new artists to gain popularity might bring many essential information for the society, and especially performers.

Overall, this research aimed to present that different types of users might receive more diverse music content. Even though the results indicated no significant differences, optimistically the theories, methodology and reflections from this study can serve as guidance for future scholars.

References:

Aguiar, L. (2017). Let the music play? Free streaming and its effects on digital music consumption. *Information Economics and Policy, 41,* 1-14, https://doi.org/10.1016/j.infoecopol.2017.06.002

Arditi, D. (2017). Digital subscriptions: the unending consumption of music in the digital era. *Popular Music and Society, 41*(3), 302-318. https://doi.org/10.1080/03007766.2016.1264101

Babbie, E. R. (2017). The logic of sampling. In M. Kerr (Eds.), *The Basics of Social Research* [online book]. Retrieved from: https://drive.google.com/drive/folders/0B_gRTYPb1bfxUnUxY3kzNG1VY1E

Bakalov, F., Meurs, M. J., König-Ries, B., Sateli, B., Witte, R., Butler, G., Tsang, A. (2013). An Approach to Controlling User Models and Personalization Effects in Recommender Systems. IUI'13.

Boyd, C. (2019). How Spotify recommends your new favourite artist. *Medium.* Retrieved from: https://towardsdatascience.com/how-spotify-recommends-your-new-favorite artist8c1850512af0

Bozdag, E. (2013). Bias in algorithmic filtering and personalization. *Ethics and Information Technology, 15,* 209-227. https://doi.org/10.1007/s10676-013-9321-6

Brennen, B. S. (2017). Qualitative research methods for media studies. New York, London: Routledge.

Bryman, A. (2012). Social research methods. New York: Oxford University Press Inc.

Castells, P., Hurley, N. J., & Vargas, S. (2015). Novelty and Diversity in Recommender Systems. Recommender Systems Handbook, 881–918. https://doi.org/10.1007/978-1 489976376_26

Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-Dependent Algorithm Aversion. *Journal of Marketing Research,* 1-17, http://dx.doi.org/10.1177/0022243719851788

Ciocca, S. (2017). How does Spotify know you so well? *Medium.* Retrieved from: https://medium.com/s/story/spotifys-discover-weekly-how-machine-learning-finds-your-new-music-19a41ab76efe

Chun, S. Y., & Hahn, M. (2006). Network externality and future usage of Internet services. *Internet Research, 17*(2), 156-168, https://doi.org/10.1108/10662240710737013

Datta, H., Knox, G., & Bronnenberg, B. J. (2017). Changing Their Tune: How Consumers' Adoption of Online Streaming Affects Music Consumption and Discovery. *Marketing Science, 37*(1), 5-21, https://doi.org/10.1287/mksc.2017.1051

De Silva, M. (2019). Spotify is still the king of music streaming – for now. *Quartz*. Retrieved from: https://qz.com/1736762/spotify-grows-monthly-active-users-and-turns profitshares-jump-15percent/.

Dubois, E., & Blank, G. (2018). The echo chamber is overstated: the moderating effect of political interest and diverse media. *Information, Communication & Society,21*(5), 729-745, http://dx.doi.org/10.1080/1369118X.2018.1428656

Fink, A. (2003). *A survey handbook*. Thousand Oaks: SAGE Publications, Inc. https://doi.org/10.4135/9781412986328

Flaxman, S., Goel, S., & Rao, J. M. (2016). Filter bubbles, echo chambers, and online news consumption. *Public Opinion Quarterly, 80,* 298–320. https://doi.org/10.1093/poq/nfw006.

Fleischer, R., & Snickars, P. (2017). Discovering Spotify—A Thematic Introduction. *Culture Unbound, 9*(2), 130–145.

Garcia-Gathright, J., St. Thomas, B., Hosey, C., Nazari, Z., & Diaz, F. (2018). Understanding and Evaluating User Satisfaction with Music Discovery. SIGIR ’18. https://doi.org/10.1145/3209978.3210049

Giese, J. L., Cote, J. A. (2000). Defining consumer Satisfaction. *Academy of Marketing Science Review, 4,* Retrieved from: http://www.amsreview.org/articles/giese012000.pdf

Goldmann, M., & Kreitz, g. (2011). Measurements on the Spotify Peer-Assisted Music-on Demand Streaming System. *IEEE International Conference on Peer-to-Peer Computing,* 206-211, http://dx.doi.org/10.1109/P2P.2011.6038737

Haim, M., Graefe, A., & Brosius, H. B. (2018). Burst of the Filter Bubble?, *Digital Journalism, 6*(3), 330-343, https://doi.org/10.1080/21670811.2017.1338145

Helberger, N., Karppinen, K., & D’Acunto, L. (2018). Exposure diversity as a design principle for recommender systems. *Information, Communication & Society, 21*(2), 191-207, http://dx.doi.org/10.1080/1369118X.2016.1271900

Hijikata, Y., Shimizu, T., & Nishida, S. (2009). Discovery-oriented Collaborative Filtering for Improving User Satisfaction. *In Proceedings of the 14th international conference on Intelligent user interfaces*, 67–76, https://doi.org/10.1145/1502650.1502663

Hosanagar, K., Fleder, D., Lee, D., & Buja, A. (2013). Will the Global Village Fracture Into Tribes? Recommender Systems and Their Effects on Consumer Fragmentation. *Management Science, 60*(4), 805-823. http://dx.doi.org/10.1287/mnsc.2013.1808

IFPI, (2019). Music Listening 2019. A look at how recorded music is enjoyed around the world. *IFPI.* Retrieved from: https://www.ifpi.org/downloads/Music-Listening 2019.pdf

Kamehkhosh, I., Jannach, D., & Bonnin, G. (2019). Effects of recommendation on the playlist creation behavior of users. *User modeling and user-adapted interaction.* https://doi.org/10.1007/s11257-019-09237-4.

Kim, J., Nam, C., & Ryu, M. H. (2017). What do consumers prefer for music streaming services?: a comparative study between Korea and US. *Telecommunication Policy, 41*, 263-272. http://dx.doi.org/10.1016/j.telpol.2017.01.008

Kjus, Y. (2016). Musical exploration via streaming services: The Norwegian experience. *Popular Communication, 14*(3), 127-136. http://dx.doi.org/10.1080/15405702.2016.1193183

Kompan, M., & Bieliková, M. (2013). Context-based Satisfaction Modelling for Personalized Recommendations. *8th International Workshop on Semantic and Social Media Adaptation and Personalization.*

Kreitz, G., & Nimela, F. (2010). Spotify – Large scale, low latency, P2P music-on-demand streaming. *IEEE P2P*.

Kunaver, M., & Požrl, T. (2017). Diversity in recommender systems – A survey. *Knowledge Based Systems, 123*, 154-162. http://dx.doi.org/10.1016/j.knosys.2017.02.009.

L'Huillier, A., Castagnos, S., & Boyer, A. (2015). Understanding usages by modelling diversity overtime. *22nd Conference on User Modeling, Adaptation and Personalization.*

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, *151*, 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005

Longoni, C., Bonezzi, A., & Morewedge, C. (2019). Resistance to Medical Artificial Intelligence. *Journal of Consumer Research, 46*(4), 629–650, https://doi.org/10.1093/jcr/ucz013.

Matthews, B. & Ross, L. (2010). Research methods: A practical guide for the social sciences. Harlow: Pearson.

McCourt, T., & Zuberi, N. (2016). Music and discovery. *Popular Communication, 14*(3), 123-126, http://dx.doi.org/10.1080/15405702.2016.1199025

Mehrotra, R., Lalmas, M., Kenney, D., Lim-Meng, T., & Hashemian, G. (2019). Jointly Leveraging Intent and Interaction Signals to Predict User Satisfaction with Slate Recommendations. *International World Wide Web Conference Committee*.

https://doi.org/10.1145/3308558.3313592

Morris, J. W., & Powers, D. (2015). Control, curation and musical experience in streaming music services. *Creative Industries Journal*, *8*(2), 106–122. https://doi.org/10.1080/17510694.2015.1090222.

Möller, J., Trilling, D., Helberger, N., & van Es, B. (2018). Do not blame it on the algorithm: an empirical assessment of multiple recommender systems and their impact on content diversity. *Information, Communication & Society, 21*(7), 959-977, https://doi.org/10.1080/1369118X.2018.1444076.

Nanou, T., Lekakos, G., & Fouskas, K. (2010). The effects of recommendations' presentation on persuasion and satisfaction in a movie recommender system. *Multimedia Systems.* 219-230. https://doi.org/10.1007/s00530-010-0190-0

Neuman, W. L. (2014). Social research methods: Qualitative and quantitative approaches (7. ed., Pearson new internat. ed). Harlow: Pearson.

Önkal, D., Goodwin, P., Thomson, M., Gönül, S., & Pollock, A. (2009). The relative influence of advice from human experts and statistical methods on forecast adjustments. *Journal of Behavioral Decision Making*, *22*(4), 390-409. doi:10.1002/bdm.637

Pallant, J. (2007). *SPSS Survival Manual.* Maidenhead: Open University Press.

Perkins, S. W. (1993). Measuring customer satisfaction: A comparison of buyer, distributor, and salesforce perceptions of competing products. *Industrial Marketing Management, 22*, 247-254.

Prey, R. (2017). Nothing personal: algorithmic individuation on music streaming platforms. *Media, Culture & Society, 40*(7), 1086-1100, https://doi.org/10.1177/0163443717745147

Prey, R. (2019). Knowing me, knowing you: Datafication on music streaming platforms. In M. Ahlers, L. Grünewald-Schukalla, M. Lücke, M. Rauch. (Eds.) *Big Data und Musik*. https://doi.org/10.1007/978-3-658-21220-9_2

Prior, M. (2009). Improving Media Effects Research through Better Measurement of News Exposure. *The Journal of Politics, 71*(3), 893–908, https://doi.org/10.1017/S0022381609090781

Promberger, M., & Baron, J. (2006). Do Patients Trust Computers? *Journal of Behavioral Decision Making*, *19*(5), 455–68, https: //doi.org/10.1002/bdm.542

Slaney, M., & White, W. (2006). Measuring playlist diversity for recommendation systems. *In Proceedings of the 1st ACM workshop on Audio and music computing* *multimedia (AMCMM '06)*. 77–82. https://doi.org/https://doi.org/10.1145/1178723.1178735

Qualtrics. (2020). How to create a great survey? Retrieved from: https://www.qualtrics.com/experience-management/research/survey-basics/

Ricci, F., Rokach, L., & Shapira, B. (2010). Introduction to Recommender Systems Handbook. https://doi.org/10.1007/978-0-387-85820-3_1.

Schedl, M., & Hauger, D. (2015). Tailoring music recommendations to users considering diversity, mainstreamness, and novelty. *The 38th International ACM SIGIR Conference*. 947-950. https://doi.org/10.1145/2766462.2767763.

Shaffer, V. A., Probst, C. A., Merkle, E. C., Arkes, H. R., & Medow M. A. (2013). Why Do Patients Derogate Physicians Who Use a Computer-Based n Diagnostic Support System? *Medical Decision Making, 33*(1), 108–18.

Spotify. (2020a). Company Info. *Spotify.* Retrieved from: https://newsroom.spotify.com/company-info/

Spotify. (2020b). What subscription do you offer? *Spotify.* Retrieved from: https://support.spotify.com/us/account_payment_help/subscription_options/subscripti nlevel/

Spotify. (2020c). For the Record. *Spotify*. Retrieved from: https://newsroom.spotify.com/2018 1102/our-spotifycheatsheet-4ways-to-find-your-next-favorite-song/

Statista. (2020a). *Number of Spotify monthly active users (MAUs) worldwide from 1st quarter 2015 to 3rd quarter 2019.* [Data set]. Retrieved from: https://www.statista.com/statistics/367739/spotify-global-mau/

Statista. (2020b). *Global digital population as of January 2020.* [Data set]. Retrieved from: https://www.statista.com/statistics/617136/digital-population-worldwide/

Tang, M. C., & Yang, M. Y. (2017). Evaluating music discovery tools on Spotify: the role of user preference characteristics. *Journal of Library and Information Studies*, *15*(1), 1 16. http://dx.doi.org/10.6182/jlis.2017.15(1).001

Tintarev, N., Lofi, C., & Liem, C. C. S. (2017). Sequences of Diverse Song Recommendations. An Exploratory Study in a Commercial System. UMAP '17. http://dx.doi.org/10.1145/3079628.3079633

Tepper, S. T., & Hargittai, E. (2009). Pathways to music exploration in a digital age. *Poetics, 37,* 227-249, https://doi.org/10.1016/j.poetic.2009.03.003

Thomsen, T. P. (2013). An economic analysis of online streaming music services. *Information Economics and Policy, 25,* 81-91, http://dx.doi.org/10.1016/j.infoecopol.2013.04.001.

Thurman, N., Moeller, J., Helberger, N., & Trilling, D. (2019). My Friends, Editors, Algorithms, and I. *Digital Journalism*, *7*(4), 447-469, http://dx.doi.org/10.1080/21670811.2018.1493936

Trefzger, T., Rose, M., Baccarella, C., & Voigt, K. (2015). Streaming killed the download star! How the business model of streaming services revolutionizes music distribution. *Journal of Organizational Advancement*, *7*(1), 29-39.

Van Selem, M., & Jankowski, N. W. (2006). Conducting online survey. Quality & Quantity, 40, 435-456. http://dx.doi.org/10.1007/s11135-005-8081-8

Waelbroeck, P. (2013). Digital Music: Economic Perspectives. *Handbook of the Digital Creative Economy, Forthcoming.*389-398, *http://dx.doi.org/10.2139/ssrn.2249690*

Wlömert, N., & Papies, D. (2016). On-demand streaming services and music industry revenues – insights from Spotify’s market entry. *International Journal of Research in Marketing*, *33*, 314-327. http://dx.doi.org/10.1016/j.ijresmar.2015.11.002

Yeomans, M., Shah, A., Mullainathan, S., & Kleinberg, J. (2019). Making sense of recommendations. *J Behav Dec Making*, *32*, 403–414, https://doi.org/10.1002/bdm.2118

Ziegler, C., McNee, S. M., Konstan, J. A., & Lausen, G. (2005). Improving recommendation lists through topic diversity. *Proceedings of the 14th International Conference on World Wide Web.* 22-32. https://doi.org/10.1145/1060745.1060754

Appendix A. Survey

Spotify and differences between users

Start of Block: Consent form

Welcome to the research study!

We are interested in understanding the differences between users of Spotify and the influence of the Discover Weekly on music diversity. You will be presented with information relevant to listening to music on Spotify and asked to answer some questions about it.

Please be assured that your responses will be kept completely **confidential**. Moreover, there are **no risks associated** with participating in this survey.

The study should take you around **10 minutes** to complete, and your participation in this research is voluntary. You have the right to withdraw at any point during the study, for any reason, and without any prejudice. If you would like to contact the Principal Investigator in the study to discuss this research, please e-mail: 507322kd@eur.nl.

By clicking the button below, you acknowledge that your participation in the study is voluntary, you are 18 years of age, and that you are aware that you may choose to terminate your participation in the study at any time and for any reason.

Please note that this survey will be best displayed on a laptop or desktop computer. Some features may be less compatible for use on a mobile device.

Thank you so much for your participation in the survey, your contribution is very important to us!

1. I consent, begin the survey (1)
2. I do not consent, I do not wish to participate (2)

Skip To: End of Survey If QID39 = I do not consent, I do not wish to participate

End of Block: Consent form

Start of Block: Do you have an account on Spotify?

Q1 Do you have an account on Spotify?

3. Yes (1)
4. No (2)

Skip To: End of Survey If Q1 = No

Q2 Please type in the box below how many hours per week do you listen to Spotify, on average?

____

Q3 Please indicate to what extent do you agree or disagree with the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I perceive myself as a heavy music listener (1)	5.	6.	7.	8.	9.	10.	11.
I perceive myself as a light music listener (2)	12.	13.	14.	15.	16.	17.	18.
I consider myself a heavy user of Spotify (3)	19.	20.	21.	22.	23.	24.	25.
I consider myself a light user of Spotify (4)	26.	27.	28.	29.	30.	31.	32.

Q4 Please indicate to what extent do you agree or disagree with the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I use Spotify to play music in the background (1)	33.	34.	35.	36.	37.	38.	39.
I use Spotify to play music that matches my current mood or activity (2)	40.	41.	42.	43.	44.	45.	46.
I use Spotify to quickly access playlists or saved music (3)	47.	48.	49.	50.	51.	52.	53.
I use Spotify to discover new music (4)	54.	55.	56.	57.	58.	59.	60.
I use Spotify to save new music or follow new playlist (5)	61.	62.	63.	64.	65.	66.	67.
I use Spotify to explore artists or albums (6)	68.	69.	70.	71.	72.	73.	74.

Q5 Please indicate, what is your favorite music genre (you can select more than one answer):

- Pop (1)
- Rock (2)
- Hip-Hop/Rap/Trap (3)
- Electronic (4)
- Techno (5)
- House (6)
- Latin (7)
- Soul/Blues (8)
- Classical/Opera (9)
- R&B (10)
- Punk (11)
- Indie Rock (12)
- Country (13)
- Metal (14)
- Other (please type) (15) ____

Q6 How often do you listen to the music from the Discover Weekly playlist on Spotify?

75. Daily (1)
76. 4-6 times a week (2)
77. 2-3 times a week (3)
78. Once a week (4)
79. Never (5)

Display This Question:

If Q6 != Never

Q7 Please indicate to what extent do you agree or disagree with the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I listen to Discover Weekly to play music in the background (1)	80.	81.	82.	83.	84.	85.	86.
I listen to Discover Weekly to discover new music (2)	87.	88.	89.	90.	91.	92.	93.
I listen to Discover Weekly to explore artists or albums (3)	94.	95.	96.	97.	98.	99.	100.

End of Block: Do you have an account on Spotify?

Start of Block: Music Diversity

Display This Question:

If Q6 != Never

Q8 Please indicate to what extent do you agree or disagree with the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Music provided by Discover Weekly consists of a good variety of songs (1)	101.	102.	103.	104.	105.	106.	107.
Music provided by Discover Weekly consists of a good variety of music genres (2)	108.	109.	110.	111.	112.	113.	114.
Music provided by Discover Weekly consists of a good variety of artists (3)	115.	116.	117.	118.	119.	120.	121.

Display This Question:

If Q6 != Never

Q9 Please indicate to what extent do you agree or disagree with the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I am often familiar with the songs that are suggested to me by Discover Weekly (1)	122.	123.	124.	125.	126.	127.	128.
Discover Weekly provides me with music content that I do not recognize (2)	129.	130.	131.	132.	133.	134.	135.
I am often familiar with the artists that are suggested to me by Discover Weekly (3)	136.	137.	138.	139.	140.	141.	142.
Discover Weekly provides me with artists that I do not recognize (4)	143.	144.	145.	146.	147.	148.	149.
Content that is recommended by Discover Weekly allows me to discover new songs (5)	150.	151.	152.	153.	154.	155.	156.
Content that is recommended by Discover Weekly allows me to explore new music genres (6)	157.	158.	159.	160.	161.	162.	163.

Content that is recommended by Discover Weekly allows me to explore new music artists (7)	164.	165.	166.	167.	168.	169.	170.
I think that Discover Weekly provides me with diverse content (8)	171.	172.	173.	174.	175.	176.	177.
The artists I see on Discover Weekly and my music on Spotify are different (9)	178.	179.	180.	181.	182.	183.	184.
I see a variety of music genres between my music on Spotify and Discover Weekly recommendations (10)	185.	186.	187.	188.	189.	190.	191.

End of Block: Music Diversity

Start of Block: Algorithmic Appreciation and Aversion

Q10 Please indicate to what extent do you agree or disagree with the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Songs recommended to me by my friends and family usually match my music taste (8)	192.	193.	194.	195.	196.	197.	198.
Songs recommended to me by media and music experts usually match my music taste (9)	199.	200.	201.	202.	203.	204.	205.
Songs recommended to me by Spotify usually match my music taste (10)	206.	207.	208.	209.	210.	211.	212.

Q11 Please indicate to what extent do you agree or disagree with the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Having algorithmic recommendations from Discover Weekly is a good way to find new music (1)	213.	214.	215.	216.	217.	218.	219.
Having songs recommended for me by editors and music journalists is a good way to find new music (2)	220.	221.	222.	223.	224.	225.	226.
Having songs recommended for me by my friends is a good way to find new music (3)	227.	228.	229.	230.	231.	232.	233.

Q12 Please indicate to what extent do you agree or disagree with the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I appreciate the recommendations provided to me by Spotify in Discover Weekly playlist (1)	234.	235.	236.	237.	238.	239.	240.
I think that recommendations provided to me by algorithms on Spotify are predicting my music taste (2)	241.	242.	243.	244.	245.	246.	247.
I do not believe that algorithms can provide me with music that is fitting my preferences (3)	248.	249.	250.	251.	252.	253.	254.

End of Block: Algorithmic Appreciation and Aversion

Start of Block: Algorithmic Satisfaction

Q13 In general, how dissatisfied or satisfied are you with your experience using Spotify to listen to the music?

255. Extremely dissatisfied (8)
256. Somewhat dissatisfied (9)
257. Neither satisfied nor dissatisfied (10)
258. Somewhat satisfied (11)
259. Extremely satisfied (12)

Display This Question:

If Q6 != Never

Q14 In general, how dissatisfied or satisfied are you with your experience using Discover Weekly?

260. Extremely dissatisfied (8)
261. Somewhat dissatisfied (9)
262. Neither satisfied nor dissatisfied (10)
263. Somewhat satisfied (11)
264. Extremely satisfied (12)

Display This Question:

If Q6 != Never

Q15 How well or poorly does Discover Weekly playlist meet your music needs?

265. Not well at all (1)
266. Slightly well (2)
267. Moderately well (3)
268. Very well (4)
269. Extremely well (5)

Display This Question:

If Q6 != Never

Q16 How well or poorly does Discover Weekly playlist match your music tastes?

270. Not well at all (1)
271. Slightly well (2)
272. Moderately well (3)
273. Very well (4)
274. Extremely well (5)

Display This Question:

If Q6 != Never

Q17 Please indicate to what extent do you agree or disagree with the following statements:

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Most of the time I enjoy the selection of music provided by Discover Weekly (1)	275.	276.	277.	278.	279.	280.	281.
Discover Weekly playlists are not enjoyable to me (2)	282.	283.	284.	285.	286.	287.	288.
The recommendations by Discover Weekly usually are a good fit for my taste (3)	289.	290.	291.	292.	293.	294.	295.
The suggestions made by Discover Weekly do not match my music preferences (4)	296.	297.	298.	299.	300.	301.	302.

End of Block: Algorithmic Satisfaction

Start of Block: Demographics

Q18 Which type of subscription to Spotify do you have?

303. Freemium (advertisement based) (1)
304. Premium (paid subscription) (2)

Q19 What is your gender?

305. Male (1)
306. Female (2)
307. Other (3)
308. Rather not say (4)

Q20 What is your year of birth?

____

Q21 In which country do you currently reside?

▼ Afghanistan (1) ... Zimbabwe (1357)

Q22 What is the highest level of school you have completed or the highest degree you have received?

309. Less than high school degree (1)
310. High school graduate (high school diploma or equivalent including GED) (2)
311. Some college but no degree (3)
312. Associate degree in college (2-year) (4)
313. Bachelor's degree in college (4-year) (5)
314. Master's degree (6)
315. Doctoral degree (7)
316. Professional degree (JD, MD) (8)

Q23 Do you have any comments, questions, or concerns regarding this survey? (answering is optional)

____

____

____

____

____

End of Block: Demographics