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Discovering music in the streaming era

How online recommendation engines and application design influence users' habits and discoveries in online music streaming services

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Abstract

The rise of online music streaming services such as *Spotify, Tidal,* and *Apple Music* has, since the late 2000s taken over as the most common way for music to be consumed. The trend is to no longer own our music, in the form of physical CDs, cassettes, vinyl, or even digital copies, but to use an online streaming service to access any music at any time. The streaming platforms also enable artists to publish music at a higher rate than before, and this increased output of content often results in issues regarding sorting and filtering. The streaming platforms' solution to such issues is implementing recommendation engines that rely on user-data fuelled algorithms and intelligent application design. While such engines are implemented to solve problems, aiming to enhance the consumer experience, one cannot ignore the potentially negative effects.

The aim of this thesis was to uncover the effects of online recommendation engines, and user experience design on users of the online music streaming service platform *Spotify*, and to understand how music streaming platforms are changing how we consume and discover music. Through analysis of the music streaming platform *Spotify* and a quantitative survey of user habits and experiences with the music streaming platform.

This thesis consists of three main parts. The first main part of this thesis is about recommendation engines, which entails the history of recommendation engines, how recommendation engines work, how the recommendation engines of *Spotify* work, and the different types of recommendation engines. The second main part is an analysis of *Spotify*, which focuses on looking at the platform through key design theories and identifying the important features of the platform, which make it unique in its field. The third and perhaps most crucial main part of this thesis consists of a quantitative survey of user habits and experiences with the music streaming platform *Spotify*.

Keywords
Digital culture, online music streaming services, Spotify, Tidal, Apple Music, iTunes, recommendation engines, recommendation systems, user experience design, user interface design, quantitative survey, Michael Schrage, Gestalt theory, Jakobs Law of Internet User Experience.

Sammendrag

Framveksten av nettbaserte musikkstrømmetjenester som *Spotify, Tidal*, og *Apple Music* har siden slutten av 2000-tallet tatt over som den vanligste måten å konsumere musikk på. Trenden er å ikke lenger eie musikken vår, i form av fysiske CD-er, kassetter, vinyl, eller til og med digitale kopier, men å bruke en nettstrømmetjeneste for å få tilgang til musikk når som helst. Strømmeplattformene gjør det også mulig for artister å publisere musikk i høyere hastighet enn før, og denne økte produksjonen av innhold resulterer ofte i problemer med sortering og filtrering. Strømmeplatformenes løsning på slike problemer er å implementere anbefalingsmotorer som opererer ved hjelp av brukerdata-drevne algoritmer, og smart applikasjonsdesign. Mens slike motorer er implementert for å løse problemer, delvis med sikte på å forbedre forbrukeropplevelsen, kan man ikke ignorere de potensielt negative effektene.

Målet med denne oppgaven var å avdekke effekten av nettbaserte anbefalingsmotorer, og brukeropplevelsesdesign, på brukere av musikkstrømme-platformen *Spotify*, og å forstå hvordan musikkstrømme-plattformer endrer hvordan vi forbruker og oppdager musikk. Gjennom analyse av musikkstrømmeplattformen *Spotify*, og en kvantitativ undersøkelse av brukervaner og erfaringer med musikkstrømme-plattformen.

Denne oppgaven består av tre hoveddeler. Den første hoveddelen av denne oppgaven handler om anbefalingsmotorer, som innebærer historien til anbefalingsmotorer, hvordan anbefalingsmotorer fungerer, hvordan anbefalingsmotorene til *Spotify* fungerer, og de ulike typene anbefalingsmotorer. Den andre hoveddelen er en analyse av *Spotify*, som fokuserer på å se på plattformen gjennom sentrale designteorier og indentifisere de viktige egenskapene til plattformen, som gjør den unik på sitt felt. Den tredje og kanskje viktigste hoveddelen av denne oppgaven består av en kvantitativ undersøkelse av brukervaner og erfaringer med musikkstrømme-plattformen *Spotify*.

Nøkkelord

Digital kultur, nettbaserte musikkstrømmetjenester, Spotify, Tidal, Apple Music, iTunes, anbefalingsmotorer, anbefalingsalgoritmer, brukeropplevelsesdesign, brukergrensesnitt design, kvantitativ undersøkelse, Michael Schrage, Gestalt Theory, Jakobs Law of Internet User Experience.

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May 2022,

Morten Skutle.

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1. Introduction

1.1 Background

Since around the turn of the millennium, the way we create, consume, and distribute music has drastically changed due to digitalization. The process of acquiring new music has changed to the point of re-invention since the early 2000s. While one used to go to a physical store to buy physical records, in the form of cassettes, vinyl, or CDs, based on the recommendation from either people in one's social circle, reviews in the paper, or perhaps a knowledgeable individual working at the local record store, or maybe having heard it on the radio, to a fully digital experience from start to finish, with the recommendations being replaced by algorithms or design features in online music streaming services such as *Spotify*, *Tidal* or *Apple Music*. The process of acquiring new music from a music consumer perspective has been completely transformed and reinvented through several innovations in the early 2000s. From burning CDs, to illegal downloading from peer-to-peer file sharing services such as *Napster*, *BearShare,* or *LimeWire,* to the introduction of legal counterparts of such illegal file-sharing services, such as *iTunes*. The rise and fall of the mp3-players such as the *iPod*, the invention and commonality of the smartphones, which are powerful enough to run online music streaming applications, and finally, the rise of online music streaming platforms such as *Spotify, Tidal,* and *Apple Music*.

This thesis explores the rise of online music streaming services as the most common platform for music consumption today by looking at its predecessors in the digital music space, such as peer-to-peer file-sharing services, *iTunes,* and other historically significant platforms and services. However, the focus of this thesis will be on the online recommendation engines and application designs' influence on the users' habits, discoveries, and experiences on the *Spotify* platform, as well as, in a somewhat limited form, on the *Tidal* and *Apple Music* platforms.

Wigmore (2014) defines a recommendation engine as “a software that analyzes available data to make suggestions for something that a website user might be interested in, such as a book, a video, or a job, among other possibilities.” (Wigmore 2014) In the context of an online music streaming platform, a recommendation engine can be the main technical mechanism in algorithmically created personalized content based on user data, such as the *Spotify* ‘Discover Weekly’ playlist feature. Application design can be in the context of online music streaming services such as *Spotify* be a somewhat broad term, which applies to everything from the aesthetics present in a platform, such as colors, logos, and themes, to design choices based on theories such as *Gestalt Theory* and *Jakob’s Law of Internet User Experience*, which will be thoroughly discussed, later in this thesis. However, at the core of this thesis focuses on the interplay and symbiosis between online recommendation engines and application design and how they both contribute to amplifying the effects of their influence, by being interwoven with each other.

1.2 Research goals and scope

My main research question in this thesis is “How is *Spotify* as a music streaming platform changing how we consume and discover music?” This thesis addresses this question different angles of approach, from an algorithmic perspective when looking at the effect of online recommendation engines within the *Spotify* platform, to design-based recommendation based on user interface design theory and figures, and the interpretation of data collected from a quantitative survey created for this thesis. I concluded that including three sub-questions to the main research questions would help highlight these different angles of approach to the main research question will help answer it from their respective perspectives. The three sub-questions are: “How do online recommendation engines shape human behavior?”, “Are users aware of to which extent their decisions are affected by recommendation engines and user experience design?” and “How does user experience design on a platform such as *Spotify* amplify change in human behavior and decision making?”. The methodology through which these questions will be answered in, will be elaborated on in the second chapter of this thesis.

1.3 Relevance

Because of the development of online music streaming services such as *Spotify*, as well as smartphones and fast mobile internet speed becoming the norm, we now live in a society where over 82 million songs and more than 4 million podcast titles are available to us almost instantaneously, on the *Spotify* platform. *Spotify* describes itself as “the world’s most popular audio streaming subscription service with 422 million users, including 182 million subscribers, across 183 markets.” (Spotify, 2022). This makes *Spotify* the most used platform for music consumption in the world.

Looking at how an online music streaming platform such as *Spotify* is affecting its user through its algorithmic recommendations and design-based recommendations, is something that I would argue holds high cultural importance, due to the potential cultural impact *Spotify* has had on music. Online music streaming services are also a quite new phenomenon, with *Spotify* launching in 2008. As a result of this, there have not been many studies with similar angles of approach as this thesis, at the time of writing it. Kiberg (2019) argues that “the technological development speed often exceeds traditional research processes (which are often lengthy and retrospective), and that the few thorough and in-depth studies done on algorithmic systems can quickly end up being irrelevant or outdated” (Kiberg 2019). Perhaps Kiberg (2019) is correct, and the fast pace of technological development can be the reason why research in this particular area of algorithmic recommendations which is somewhat lacking compared to other more traditional researchable objects and occurrences.

1.4 Thesis structure

After this introduction, Chapter 2, 'Methodology' will present the main research question and sub-questions and show how I will answer them throughout this thesis. It will describe the procedure and methodology of each chapter of the thesis and introduce the key theoretical frameworks that is the foundation for the rest of the thesis chapters will also be presented. This chapter will also include a section about the decision to do a quantitative survey as one of the key research fundaments in this thesis, a section about ethical considerations regarding the use of the survey in this thesis, and potential bias in the survey sample.

In Chapter 3, 'Recommendation engines,' I will go through the history of recommendation engines, all the way from 'offline recommendation engines' from the pre-digital era to the development of early online recommendation engines such as *Tapestry, GroupLens,* and *Ringo*, and how they have had an importance on the current online recommendation engines of the online music streaming services. There will also be an emphasis on the first digital online music services and the road from illegal downloading, to iTunes, to today's online music streaming services. Chapter 3 'Recommendation engines' will also focus on how recommendation engines work within online music streaming services, such as the 'Discover Weekly' feature in *Spotify,* and the differences between personalized / non-personalized, and algorithmic / design-based recommendations. I will also reveal a small experiment I did while writing this thesis, where I attempted to trick the recommendation engines of *Spotify* into making a very specific type of recommendations. The concept of 'Blackboxing' in algorithmic recommendations will also be examined.

The primary focus of Chapter 4, 'Analysis of Spotify,' is to do a descriptive and design analysis of *Spotify*, in addition to making a comparison between the functionality and design of the three online music streaming services*: Spotify, Tidal,* and *Apple Music*. Design impact on recommendation engines will also be discussed, as well as the Spotify platform's cultural power and influence. *Spotify's* role in the amateurization and democratization of music will also briefly be presented.

Chapter 5, 'Quantitative surveys,' will be dedicated to presenting and discussing the answers from the English/International and Norwegian versions of the quantitative survey I created for this thesis. The sixth and final chapter of this thesis will be the 'Conclusion' chapter. It will contain a summary of the key research findings about research goals and research questions, as well as the value and contribution thereof. There will also be sections about limitations in the thesis, as well as research possibilities.

2. Methodology

I will, in this methodology chapter, present the research questions of this thesis and explain how I will answer them throughout this thesis. The procedure and methodology of each chapter of this thesis will also be reviewed and explained the reasoning behind, this methodology chapter. The key theoretical framework, as research methods behind each chapter, and the thesis will also be presented in this chapter.

2.1 Research methods

The main goal of this thesis is to get a better understanding of how the combination of online recommendation engines and platform design are influencing users' listening habits and discoveries. Developing a straightforward **main** research question for this thesis has been a necessary process. The main research question will be part, be answered primarily through analyzing the answers from an English/international and a Norwegian quantitative **survey** which I created for this thesis, as well through a thorough analysis of **design**, and **online recommendation engine** elements of *Spotify*, and comparing *Spotify* to two rivals in the online music streaming service marked *Tidal* and *Apple Music*. Analysis of historical predecessors and pioneers within the digital music, and recommendation engine areas, will also be done to explain how the online music streaming service platform *Spotify* has been able to develop into the online recommendation engine fueled industry leading platform it is today.

This thesis also consists of three sub-questions to the main overarching research question. This ‘sub-question’ method was chosen due to its ability to show how different aspects of the *Spotify* platform, such as online recommendation engines, platform design, and user awareness of the effects of online recommendation engines and user experience design, can contribute toward answering the main research question.

2.2 Main research question and sub-questions

My main research question for this thesis is:

“How is *Spotify* as a music streaming platform changing how we consume and discover music?”.

The three sub-questions to the main research question are:

1) “**How do online recommendation engines shape human behavior?”**
2) **“Are users aware of to which extent their decisions are affected by recommendation engines and user experience design?”**
3) **“How does user experience design on a platform such as *Spotify* amplify change in human behavior and decision making?”**.

1) “How do online recommendation systems shape human behavior?”

The impact and importance of the combination between interaction design and user-data fueled algorithms cannot be understated. That is why the analysis of *Spotify* in this thesis will focus on the interaction design of the *Spotify* platform, and the online recommendation engine aspects. This question will be answered partly through chapters four and five, ‘Analysis of Spotify’ and ‘Quantitative survey’, however, the most relevant chapter which discusses themes related to this question is the chapter three, ‘Recommendation engines.’

2) “Are users aware of to which extent their decisions are affected by recommendations engines and user experience design?”

The second sub-question in this thesis will be answered through an analysis of specific survey questions from the quantitative survey in the fifth chapter of this thesis, and through the third and fourth chapters of this thesis, ‘Recommendation engines’ and ‘Analysis of Spotify’. In the quantitative survey for this thesis, the survey respondents are being directly and indirectly asked if they either are worried about how much impact the recommendation algorithms, and user experience design are having on their ability to discover new artists/genres/podcasts. In addition to other questions which are relatable to this second sub-question.

The discussion of the answers collected from the surveys will be the primary method for answering this sub-question. However, parts from Chapter 3 and 4 will also be relevant for answering this sub-question. Discussing and discovering the history of recommendation engines, as well as the mechanisms behind current recommendation engines in online music streaming services such as *Spotify*, are integral to understanding how the users of the platform are experiencing the effects of recommendation engines on themselves. Or, if they are at all concerned about how these effects can change their abilities to discover content on online music streaming services, as well as other media platforms.

Similarly, to how discussing and discovering aspects of the *Spotify* recommendation engine, as well as historical aspects of the recommendation engines development can be relevant to answering this sub-question. Aspects of user experience design, and the effects of user experience design on the users of *Spotify* will be discussed through the analysis of *Spotify*, in the fourth chapter of this thesis.

3) "How does user experience design on a platform such as *Spotify* amplify change in human behavior and decision making?"

The third sub-question in this thesis will mostly be answered through a combination of the fourth and fifth chapters of this thesis, 'Analysis of Spotify' and 'Quantitative survey'. In similar fashion as in the second sub-question, the survey respondents of the quantitative survey for this thesis will be asked, if the user experience design on the *Spotify* platform is contributing to changing the behavior and decision making of the users on the platform.

As well as listening to the survey respondents, and their opinion as to how the user experience design on the *Spotify* platform is influencing their behavior and decision making on the platform, I will also be drawing from 'Analysis of Spotify' chapter when it comes to answering this third sub-question of the thesis.

The combination of uncovering user experience design theories that can have a significant impact on the users of the *Spotify* platform and discussing these user experience design theories in the context of the relevant answers from the quantitative survey will be the key to answering this question.

2.3 'Recommendation engines' methodology

One of the goals of the third chapter of this thesis, 'recommendation engines', is to give a precise definition of what a recommendation engine is, through definitions by Wigmore (2014), as well as examples from other online platforms such as *Amazon* and *Facebook.* Examples from within the *Spotify* platform will also be presented. There will also be drawn analogies towards the automobile industry, as well the stock market. This will be done to give the reader a better understanding as to how and what a recommendation engine has been, as well as how the current iterations of online recommendation engines came to be as a result of its offline predecessors. Online recommendation engines are based on new technology, but old ideas which predates the technology of the digital and online era.

Another important aspect of this chapter concerning this thesis is the history aspect. I will present important aspects of the history of online recommendation engines and present some of the early online recommendation engine-based systems, such as *Tapestry* and *GroupLens*, and first **online music** recommendation-based system, *Ringo*. The road from the early days of *Ringo* to the *Spotify* platform of today will also be presented, by looking at the rise of illegal peer-to-peer file-sharing software of the late 1990s and early 2000s, and the importance of Apples *iTunes.*

The theoretical framework for this section of the chapter includes Schrage (2020), which stands for some of the most meaningful citations throughout this thesis, as his book 'Recommendation Engines' serves as both an historical chronology from the birth of the online recommendation engine to the online recommendation engines of today, as well as giving insight into how the recommendation algorithms of platforms such as *Spotify*, and many more work. Another essential framework from this section includes Beato (2020) on his insight into the rise of illegal downloading of music and Berlinger and Sinofsky (2004) on the *Metallica et al. v Napster inc.* Lawsuit controversy. Wyatt Jr (2018) and Jobs (2001) will form the basis for the *iTunes* and *iPod* sections.

The next section of the 'recommendation engines' chapter will discuss how recommendation engines work in music streaming services. This will start by breaking down recommendation engines into categories such as **personalized**, **non-personalized**, **algorithmic**, and **design-based** recommendations. These distinctions are important as they represent recommendations rooted in different core aspects of the platform in which they are located. I will then go through each of these categories mentioned above and show examples of them within the *Spotify* platform. Schrage (2020) is an essential source of importation and examples. Nash (2019) and Louridas (2020) are crucial theoretical frameworks for the subject of algorithms. The use of figures, which mostly are screenshots from the *Spotify* application, is also crucial in this section to provide visual support to arguments made in the text.

After the section about the different recommendation engine categories, sections about 'Discover Weekly', 'The Frank Sinatra Experiment', and 'Blackboxing' will be presented before moving on to the next chapter in this thesis. The 'Discover Weekly' section is primarily as presentation on how the perhaps most important and popular form of recommendation within the *Spotify* platform works, and 'The Frank Sinatra Experiment' is a little experiment I did while in the writing process in this thesis, where I attempted to see if I was able to fool the 'Discover Weekly' algorithms and manipulate the features of 'Discover Weekly'. The last section of the chapter about 'recommendation engines' will discuss 'The blackboxing' of algorithmic recommendations. The theoretical framework for this section is based on Latour (1999) and will be looking into the lack of transparency and visibility of the recommendation engines of the *Spotify* platform.

2.4 'Analysis of Spotify' methodology

The purpose of the fourth chapter of this thesis is to provide a thorough analysis of *Spotify*, first through a descriptive analysis which will give the reader of this thesis an introduction to the functions, aesthetics, and layout of the *Spotify* platform, as well as explaining seven key points of interests within the *Spotify* design. Going through these seven key points of interest is to give the reader an introduction to the critical functions of the *Spotify* platform. Key theoretical framework in the descriptive analysis part of this chapter includes Thorlacius (2007) when it comes to explaining aesthetics in the context of a platform, such as *Spotify* and Golombisky and Hagen (2016) when it comes to explaining what a 'Focal point' is. However, I would argue that a key element throughout this entire chapter is the use of screenshots as figures which are referred to throughout the chapter. The importance of using visuals when analyzing a digital platform such as *Spotify* cannot be overstated due to its ability to provide the reader of this thesis with a good way of understanding the arguments made based on the functionalities of the platform.

The second part of this chapter is called 'design analysis' and will focus on user experience design, and user interface design in *Spotify*, as well as explaining how key design theories such as Gestalt Theory (Golumbisky and Hagen 2016) impact the *Spotify* users. There will also be a comparative analysis between *Spotify*, and its online music streaming service competitors *Tidal*, and *Apple Music*, through comparing the experiences of creating new account on all three platforms, as well as looking at historical aspects of the platforms, platform design, how the three platforms tackle issues such as 'The Cold-start problem' and looking at the differences in the business models of the three platforms. At the end of this chapter, I will also be looking at design aspects' impact on recommendation engines.

Key theoretical framework for this section of the chapter includes Norton (2018) and Obi (2018) when it comes to discussing UX vs UI design, Golumbisky and Hagen (2016) are a vital source of information when it comes to the section about Gestalt Theory.

Volianskyi (2019) is also essential when discussing the Gestalt principle of closure. In the sections about the cold-start problem, Nodder (2013) and Zhao (2016) are key discussion points. However, drawing parallels between *Spotify*, *Tidal*, and *Apple Music* in discussing the differences in functionality and through examples with the help of figures, is one of the most important ways of presenting the arguments. When discussing platform design, and design impact on recommendation engines, Nielsen (2017)' explanation of Jacob's Law of Internet User Experience and Burns (2019)' presentations of Pariser (2011)' concept of 'filter bubbles' are the main theoretical framework of which argumentation and conclusions can be drawn from. Many of the theoretical framework mentioned in this chapter also serves a purpose in the next chapter of this thesis, which is 'Quantitative surveys', where the questions of the survey have anchoring in both application design, and the recommendation engines of *Spotify*, in addition to other angles of approach to answer the research questions of this thesis.

2.5 'Quantitative Survey' methodology

One of the driving forces behind my choice to apply for the master's program in digital culture here at the University of Bergen, as well as one of the biggest challenges with writing this MA thesis was my underlying desire to explore practical research methods such as quantitative survey and use it in my thesis. The importance of a theoretical framework will arguably always be necessary while working on any level of a thesis. However, I would argue that a quantitative survey will be beneficial when it comes to getting answers to this thesis's research questions, exploring hypotheses, and confirming or denying stereotypes.

2.5.1 The surveys

For this thesis, I created two quantitative surveys in the fall of 2020. One in Norwegian and one in English. The main reasoning behind creating both a Norwegian survey and an English survey was to compare Norwegian users to international ones to see if there was any real difference in user behavior. For practical language reasons, since this thesis is written in English, this chapter will mainly include figures obtained from the English version of the survey.

Both surveys were created using Google Survey; however, the University of Bergen's 'SurveyXact' tool for developing surveys strongly considered in the planning section of the surveys. The preferred choice of survey tool ultimately ended up being Google Survey due to its ease of use and automatization of data visualization.

The two surveys are completely identical to each other when it comes to the questions, order of the questions, and distribution timeline. The only intended difference between the two is the language in which they are written in, and their intended target audience.

Both surveys contain twenty-four questions, where two of the questions are straightforward yes/no questions, and eight of the questions are multiple-choice questions with four to eight answer options. Ten of the questions can be defined as grading questions, where the survey participants are asked to answer the questions on a scale of one to five, where five has the highest value. Three questions are open for the survey participants to give a short answer in the form of their own words.

2.5.2 Potential bias in the survey sample, and Covid-19

The Norwegian survey has gotten 467 answers, while the English version has gotten 503 answers as of May 18th, 2021. The surveys collected answers from September 24th, 2020, to the May 2nd, 2021, and the survey participants were found via sharing the surveys on my social media accounts, as well as posting on the popular internet web forum 'Reddit,' on the 'subreddits' 'r/SampleSize' and 'r/norge.'

There is potentially a bias in the sample generated from my social media accounts since I have been involved in the music business for many years and, therefore, have many musicians and music producers as my social media connections. This may lead to specific survey questions being answered from more of an artist's perspective than a casual music listener, which would perhaps be the most typical type of survey respondent from a non-biased survey. However, I would argue that the benefits from sharing the surveys on my social media accounts, which has contributed to securing almost a thousand responses to the surveys, outweigh the potential bias which are mentioned in the text above and below due to the large number of survey respondents it has helped generate.

The subreddit 'r/SampleSize' is an internet forum for surveys and polls to be posted for research studies, as well as opinion polls, with almost two hundred thousand active members. 'r/SampleSize' is also a place for people who enjoy responding to surveys to gather and help people obtain responses for their research (Reddit 2022). 'r/norge' is the official Norwegian community on Reddit, and like 'r/SampleSize' it has almost two hundred thousand active members.

The survey sample group has a potential bias towards younger people in their mid to late twenties since most of my social media connections are of that age. There is also a potential for the survey respondents from Reddit to be biased for the same reasons. Statistics show that most 'Reddit' users are between the ages of 20-29 (Statista 2022).

Another potential reason for the survey results being biased is that the surveys collected answers during the height of the global Covid-19 pandemic. Perhaps the listening patterns of the survey respondents were, to a certain extent, affected by the lockdowns and other issues caused by the Covid-19 pandemic.

However, I would argue that the survey answers were collected during the Covid-19 pandemic could serve a purpose for future research since the results of the surveys made for this thesis can be interpreted as a snapshot of peoples listening habits during a global pandemic. Comparing the results of the surveys from this thesis to for example, surveys were done when the Covid-19 pandemic was nothing but a distant memory of the collective mind of our society could be an interesting study for future research.

2.5.3 Quantitative survey in digital culture

An argument could be made against the use of quantitative surveys in humanities studies such as digital culture. It is perhaps a quite unusual method within the humanities and is more in line with social science studies. However, the focus and purpose of the two surveys do not lie in the statistics method of social sciences, with their focus on T-tests, P-values, dataset errors, and significance levels.

Using these types of statistical analysis tools would be difficult on the surveys created for this thesis, due to the many different types of answers which is possible for the survey respondents to use throughout the survey, ranging from simple 'Yes/No' questions, to multiple choice type questions with three to eight answer alternatives, short sentence answers, and 'On a scale of 1 to 5 (5 has the highest value)' gradient type answer alternatives. I have chosen to emphasize the differences and similarities between the English/International, and Norwegian versions of the survey and the relationship between specific survey questions that are relatable to each other. There is also a focus on explaining the outcome of the survey by anchoring the arguments in theories discussed in earlier chapters of the thesis and introducing some new concepts and theories. With all the factors mentioned in the text above, I concluded that it would be difficult to use specific traditional statistical analysis tools to produce meaningful data from my surveys for this thesis.

The focus of the two surveys in relation to this thesis is get a general understanding of user behavior on the online music streaming service *Spotify*, as well as discussing the answers based on a theoretical framework which is relevant to digital culture as a field of study.

While argumentation based on the survey responses will be a substantial part of the survey chapter, there will also be drawn parallels to key theories discussed in the earlier chapters, such as ‘Path of least resistance’ (Nodder 2013), Jakob’s Law of Internet User Experiece (Nielsen 2017), aesthetic aspects (Thorlacius 2007) *Gestalt Theory* (Golumbisky and Hagen 2016) ‘Filter bubble’ (Burns 2019). As well as introducing new theories such as *The Lindy Effect* (Vervisch 2022), and *The Matthew Effect* (Bartley 2016).

These key theories will serve as argumentative anchoring when discussing the data from the twenty-four survey questions, in both the English/international and Norwegian version of the survey.

2.5.4 Ethical considerations

When it comes to ethical considerations of collecting survey answers, a disclaimer at the header of both the English/International and Norwegian versions of the survey states that ‘This survey is anonymous. The is also an effort made in this chapter when discussing the survey answers, to emphasize percentages of each answer and the majority of answers. This method of discussing survey results is helpful to keep the individual survey respondents’ anonymity further intact, as it does not single out any of the survey respondents in any way.

It has also been clearly communicated in the posts on my social media where I have shared the link to the surveys and the posts on Reddit that the survey is a hundred percent anonymous. It is also stated that the survey results will only be used in my MA thesis in digital culture at the University of Bergen.

3. Recommendation engines

In order to understand how recommendation engines work today within the context of a platform such as *Spotify*, I would argue that it is essential to understand which core ideas forerunners within the field of recommendation engines helped shape how music streaming services such as *Spotify* works today.

3.1 Recommendation engines

One might argue that the way recommendation engines work is more a direct result of normal human behavior than anything else. Even though there will be almost exclusively a focus on online recommendation engines throughout this thesis, it is arguably vital to look at ‘offline’ recommendation engines to better understand the online recommendation engines of today.

One could argue that exploring systems that have taken the journey from analog to digital and offline to online has a high value. Looking at the transition from an analog/offline system towards a digital/online system can highlight the impact of technological development and point toward which parts of the analog/offline systems have translated well into the online era of the system. It is also arguably essential to know that the origins of such systems have roots beyond the digital world we live in today. Exploring the core principles and ideas of analog/offline systems might help us understand how digital/online systems work today.

As mentioned briefly in the introduction of this thesis, Wigmore (2014) defines *recommendation engines* as: “A recommendation engine, also known as a recommender system, is software that analyzes available data to make suggestions for something that a website user might be interested in, such as a book, a video or a job, among other possibilities.” (Wigmore 2014)

An example of a recommendation engine could be Facebook's ‘People You May Know’ section, which makes friend suggestions to users based on personal data, mutual friends, geographical location and more. Another example could be Amazon’s ‘Customers Who Bought This Item Also Bought…’. An example more relevant to this thesis could be the *Spotify* ‘Discover Weekly’ playlist. ‘Discover Weekly’ is a feature that delivers an algorithmically personalized playlist to its users each week. More on these examples and how they function will be discussed further in this chapter's ‘how recommendation engines work’ section.

Before taking a deep dive into how the specific technical parts of online recommendation engines work, an understanding the core principles of recommendation engines is essential.

To take an example from the automobile industry, there would not be a technologically advanced car like a Tesla today if it were not for pioneers such as Henry Ford and Carl Benz’s development of what we today would acknowledge as the first cars. The technological differences between a Tesla Model 3 and a Ford Model T are enormous. However, the two products' functionality and purpose are the same.

One can perhaps build on the same principles from the car analogy when it comes to the field of recommendation engines. The core principles of analyzing information about someone or something and then using that information to present either a product to the right target audience or to point someone in the direction of something they are interested in is still the core of a recommendation engine.

When discussing today's recommendation engines, there would undoubtedly be an assumption that one is discussing **online** recommendation engines and buzzwords such as machine learning, artificial intelligence, user data, algorithms, and much more. The logical next step might be to assume then that the existence of recommendation engines is only possible with the existence of the internet and computing power.

While this is primarily true when thinking about recommendation engines of today’s complexity and standards, there have been many different types of recommendation systems which were able to operate before the invention of the internet. Looking at these pre-internet recommendation systems is essential, as they are the foundation on which modern online recommendation engines are based. To easily differentiate between pre-internet recommendation systems and online recommendation engines, pre-internet recommendation systems will be referred to as offline recommendation engines or offline recommendation systems.

3.2 Offline recommendation engines

Humanity and the society we live in are inarguably a result of choices. Choices that we as individuals have made and choices made by governments and large companies. Our choices arguably reflect who we are as individuals and in societies. Nevertheless, where do these choices come from? Are they all a direct product of free will, critical thinking, and individual decision-making?

One could argue that they are not, at least not, one hundred percent autonomous. The point important to highlight is that we as individuals are being nudged towards making certain decisions, based on the decisions and advice from people in our social circle, trends in society, as well as our interaction with technologies such as apps or websites which use some sort of recommendation engine.

Before delving into the different types of online recommendation engines, it is essential to acknowledge their predecessors to understand the present-day online recommendation engine better.

The existence of offline recommendation engines is based on some of the same core principles as an online recommendation engine. The core of any recommendation system is data and examples of people and organizations that have made decisions or recommendations based on data.

3.2.1 Stock market analyst example

Take, for example, the stock market. It had existed in some way, shape, or form for centuries, long before computing and communication technologies made it possible to take part in stock exchanges through the internet. However, how does the stock market work, and why is it relevant to today's online recommendation engines?

"The concept behind how the stock market works is pretty simple. Operating much like an auction house, the stock market enables buyers and sellers to negotiate prices and make trades. […] **Supply and demand** help determine the price for each security, or the levels at which stock market participants – investors and traders – are willing to buy or sell" (O'Shea and Davis 2021).

While the supply and demand help determine the stock prices, the real key part of this stock market recommendation engine analogy is the stock market analysts.

"Stock analysis is a method for investors and traders to make buying and selling decisions. By studying and evaluating **past and current data**, investors and traders attempt to gain an edge in the markets by making informed decisions." (Chen et al 2021). Since stock analysts are making recommendations for investors and traders based on evaluating data, people working as stock analysts during the offline era can be but in the category of offline recommenders.

3.4 History of online recommendation engines

One could reasonably argue that the history of online recommendation engines is closely connected to the birth of the internet as we know it today. With the world wide web development, the information flow rapidly increased. With technology such as e-mail and online collaborative efforts, the amount of data that requires sorting and filtering has only increased. They will most likely continue to increase as the internet grows and expands to more and more platforms.

In today's world, one might think of online recommendation engines as a piece of technology that helps massive companies increase their profits by making calculated recommendations. Alternatively, entertainment and music companies like *Netflix* or *Spotify* use their recommendation engines to improve their platforms, thus improving the user experience on said platform or maximizing the time users spend on said platforms.

Perhaps online recommendation engines can benefit both the users and the platforms today. The true agenda of an online recommendation engine within a platform depends on which perspective one is looking at it with. However, decades before it was typical for the average internet user to deal with online recommendation engines as a part of their everyday lives, online recommendation engines got their start in academia and research.

In the following section, there will be a brief explanation of two of the first online recommendation engine-based systems spawned out of research and academic needs, *Tapestry* and *GroupLens*. There will also be a brief introduction to one of the first online music recommendation engine-based systems, *Ringo*. Tapestry and *GroupLens*' importance as forerunners within the world of online recommendation engines cannot be understated. Without them, there would probably not be a system for a platform such as *Ringo* to exist. Furthermore, without *Ringo*, who knows? Perhaps we would not have the pleasure of having music streaming platforms as we know them today.

3.4.1 Tapestry

Even though one might think of online recommendation engines as the foundation of modern e-commerce, online recommendation engines were created by and for scientists and academics. The birth of the online recommendation engines can be traced back to *Tapestry*, created by Xerox's Palo Alto Research Center in California. *Tapestry* was, at its core, an experimental mail system that let the users subscribe to email lists that interested them. The intention behind the *Tapestry* system was to help the users navigate through a large amount of email and data, find what was relevant for them, and keep getting the relevant emails and data from there on out. Even though one could argue that *Tapestry* was groundbreaking back in 1992, it had some issues. It required vast amounts of human effort to write annotations and specify filters. As Schrage (2020) puts it in his chapter about the history of online recommendation engines, "In real-world tests, *Tapestry* was neither easy nor automated enough. The vast majority of documents went untagged" (Schrage 2020, p. 67).

Tapestry was too complicated and required vast amounts of mundane human labor to keep up with its document annotations and filters. However, it is essential to remember that Tapestry was the first of its kind. The first online recommendation engine.

The ideas behind *Tapestry* could have served as an inspiration for future online recommendation engines. The genie was out of the box, and perhaps the possibilities of such as system became apparent to future developers.

3.4.2 GroupLens

Developed by MIT and the University of Minnesota in 1992, *GroupLens,* an article recommendation engine, was built upon the conceptual foundations of *Tapestry*. However, even *GroupLens* managed to succeed where Tapestry fell short. The ability to work as an automated collaborative filtering engine without the need for humans to perform mundane tasks such as providing annotations and filter specifications. For a research effort built to rate news articles on a scale from one to five, *GroupLens* arguably ended up being so much more.

One could frame the origins of online recommendation engines this way:

Tapestry showed the possibility of what an online recommendation engine could achieve, while *GroupLens* became an actual automated online recommendation engine. Key features of online recommendation engines such as 'correlations engine,' 'nearest neighbor' or 'neighborhood' algorithms, and the automatization of collaborative filters are critical features of modern recommendation engines that can directly be traced back to *GroupLens*. An analogy that might help explain the differences between *Tapestry* and *GroupLens* could be: Tapestry invented the wheels and gearbox. At the same time, *GroupLens* was able to invent the simple car.

3.4.3 *Ringo* (the start of online music recommendations)

Coming out of the MIT Media lab in 1994 was the first attempt at an online music recommendation, *Ringo.* Many of today's music streaming services like *Pandora*, or *Spotify*'s radio recommendations, can be directly traced to how *Ringo* used users' ratings of artists to create something the founders of *Ringo* Upendera Shardanand and Pattie Maes called Social information filtering. *Ringo* users were tasked with rating 125 artists on a scale from 1 ('Pass the earplugs') to 7 ('BOOM! One of my FAVORITE few!).

The *Ringo* system then had enough data to create a user profile and make recommendations through its Social information filtering system. *Ringo's* Social information filtering system is explained as "a filter that automates a process of 'word-of-mouth' recommendations." (Shardanand and Maes 1995). An example of how this worked in *Ringo*'s system could be if one imagines two platform users. User one like artists 1, 2, 4, and 5, while user two like artists 1, 3, 4 and 6. The proximity between the tastes of user one and user two are quite similar, and therefore could be classified as 'users in the same neighborhood' by one of *Ringo's* algorithms. The *Ringo* system would then for example recommend artists 3 and 6 to user one, and artists 2 and 5 to user two.

Today we could categorize *Ringo*'s recommendation system under the collaborative filtering type of recommendation engine. Even though the founders of *Ringo* went on to help develop other music recommendation systems such as *HOMR* (Helpful Online Music Recommendation Service) and *Firefly*, the impact on the early *Ringo* system on today's music recommendation engines is why it has a place in this thesis. It is also worth mentioning that Shardanand and Maes included *Tapestry* and *GroupLens* as important in relation to their work with *Ringo*, and one might argue that it is hard to imagine a music recommendation system such as *Ringo* existing as early as 1994, without early attempts at online recommendation engines such as *Tapestry* and *GroupLens*.

3.5 The road from *Ringo* to *Spotify*

While looking at *Ringo* as an early online music recommendation system, it is essential to think about the period in which it was created. When *Ringo* was online, users could consider the recommendations the next time they visited a music store, perhaps whether they should consider going to a concert or ordering CDs via mail. However, the key feature of *Ringo*, the music recommendation by email, is still going strong today. As shown in Figure 2.0 on the next page, an email from *Spotify* about 'new music from artists you like'. Even though the email from *Spotify* is a nudge for the user to engage in a personalized playlist, the parallels to the *Ringo* systems are apparent.

Moving forward with new ideas, technologies, and platforms, while still utilizing the ideas of predecessors within the field seems like a red thread throughout the journey from *Tapestry, GroupLens,* and *Ringo,* all the way to the music streaming services of today. However, the need for legitimate online streaming services like *Spotify*, *iTunes/Apple Music*, *Tidal*, and many more, was arguably a result of the enormous amount of music being illegally downloaded in the early 2000s.

(Figure 3.0 “Ringo to Spotify”, above)

3.5.1 Illegal downloading to music streaming

The period between 1999 and 2001 was arguably the turning point for the music industry when it came to adapting to digital technology. The events explained in this text now are not directly linked with online recommendation engines or user experience design. However, the developments within the music industry at this time period made it apparent that a legitimate way for people to access music in the online era was needed. The need for music streaming services had arrived.

The rise of peer-to-peer file-sharing software and services such as, for example *Napster, LimeWire, Kazaa, or BearShare*, allowed users to share media files such as music, videos, books and more. One could argue that the music industry was too slow to react to the rapid digitalization at the turn of the millennium and that file sharing and illegal downloading of music were a consequence of this (Beato 2020). When *Napste*r was up and running in 1999, no legal counterpart could meet user demands of ease of access to an extensive library and instant availability. Apple's *iTunes* did not launch until 2001 and did not open its online digital media store until 2003. *Netflix* was still a DVD-by-mail type company, and *Spotify* was almost a decade away from being a closed invite userbase-only type streaming service.

The first few years of the new millennium were filled with 'you would not download a car' type anti-piracy commercials in my cinemas and movie-rental places and more than a few lawsuits against file-sharing services. Several artists and record labels started suing file-sharing platforms such as *Napster*. Perhaps one of the most interesting ones was the *Metallica et al. v Napster, Inc* lawsuit in 2000. The lawsuit was one of them, if not the first case, that involved a band or an artist suing a file-sharing company.

From an outside perspective, it could have seemed like a David vs Goliath type of scenario, where the big and greedy heavy metal band was suing a relatively small software company for millions of dollars. However, as detailed by Metallica drummer Lars Ulrich in their 2004 documentary film *Metallica: Some Kind of Monster*, was that the band discovered that an unreleased demo version of their song "I Disappear" was being played on the radio, and that the leak of the unreleased demo could be traced back to *Napster* (Berlinger and Sinofsky 2004).

One of the great ironies of this lawsuit from an outsider's perspective is that Metallica themselves rose to notoriety in the early 1980s with the help of what can be considered the pre-digital way of music piracy. Bootlegged cassette tapes recorded at live shows and people copying and trading these tapes arguably helped the band land a record deal.

Perhaps the leak of unfinished songs such as “I Disappear,” combined with the feeling of lack of control and monetization, led to the lawsuit. Different lawsuits kept coming, and different peer-to-peer file-sharing services came and went. The early 2000s could be described as a giant game of ‘Whack-A-Mole’ between artists, record companies, and file-sharing companies. However, the popularity of this new way of obtaining and consuming music, movies, and other media showed one crucial thing: the entertainment industry had to adapt to this new way of media consumption to combat illegal downloading.

The world was ready for modernization and digitalization of which entertainment and art such as movies and music were being consumed, and the race towards creating legitimate ways for people to be able to do was on.

3.5.2 iTunes and iPod

In January 2001, Apple CEO Steve Jobs introduced *iTunes*. The way we buy and consume media has perhaps never been the same. As one of the earliest, if not the earliest legitimate alternatives in the online music marketplace, Apple’s *iTunes* is, in a historical sense, a critical link between the analog world of music and the online music streaming platform-dominated space of today's music consumption.

First introduced as a free, simple, and powerful digital music jukebox, *iTunes* were launched as a competitor to desktop music managers at the time, such as *RealJukeBox*, *Windows Media Player*, *musicmatch,* and *WinAmp*, which were rather unappealing and complicated to use, additionally, they throttled things such as encode quality and CD burning speed to encourage users to pay for the ‘Pro’ versions of these desktop music managers. Apple CEO Steve Jobs said at a press event when launching *iTunes* that:

“Apple has done what Apple does best – make complex applications easy, and make them even more powerful in the process. iTunes is miles ahead of every other jukebox application, and we hope its **dramatically simpler user interface will bring even more people into the digital music revolution**” (Jobs 2001).

However, it was not until the fourth update of *iTunes* in 2003 that *iTunes* became an industry leader and a pioneering force for the at the time new digital age of music. “A new user interface was added, along with the ***iTunes Music Store,*** the main contributor to *iTunes* tremendous success” (Wyatt Jr 2018). With the fourth update of *iTunes*, Apple had created the first legal digital music marketplace. One could argue that the most significant driving factor behind Apple's creation of a **legal** digital music marketplace was fueled by the popularity of illegal filesharing applications such as *Napster*, *LimeWire*, and *BearShare*. A key feature that the *iTunes Music Store* had in common with these illegal filesharing applications was the possibility of purchasing/downloading individual songs rather than entire albums.

It also must be said that the symbiosis between Apple's mp3-player, the *iPod*, and *iTunes* helped bridge the gap between legitimate digital music platforms such as *iTunes* and illegal filesharing applications. It was now as easy, if not easier, to use legitimate methods of acquiring music into one's *iPod* than to use its illegal counterparts. Prior to the introduction of the *iPod*, the mp3player marked was full of rather expensive products with minimal storage space and horrible controller design. Getting your personal music over on these horrible devices was also a challenge. This was often a slow and tedious process due to slow data transfer technology and often horrible or non-existent computer software for these mp3-players. The combination of *iTunes* and *iPod* was a digital music revolution in the early 2000s.

According to Wyatt Jr (2018), former Apple CEO Steve Jobs had faith in music consumers being willing to pay for legitimate and legal alternative to illegal filesharing applications. “We believe that 80% of the people stealing stuff don’t want to be, there’s just **no legal alternative**. So, we said, ‘**Let’s create a legal alternative to this**.’ Everybody wins. Music companies win. The artists win. Apple wins. And the user wins, because he gets a better service and doesn’t have to be a thief.” (Wyatt Jr 2018).

One could argue that *iTunes* was the first legitimate digital music platform and, in many ways, laid the foundation for online music streaming platforms to grow. The success of the *iTunes* platform showed that people were willing to pay for music on a digital platform if the platform was a good enough alternative to the illegal filesharing applications of the era. In 2019, Apple announced that the music part of *iTunes* was to be replaced by *Apple Music*, an online music streaming service that signals the end of the first era of legitimate digital music. With the growing technological capabilities of smartphones, one does not need to carry both an mp3-player and a phone. Combined with the rapid increase of wireless mobile internet technologies such as 3G and 4G, this helped usher in the era of online music streaming platforms such as *Spotify, Tidal, Apple Music*, and many more like them.

(Figure 3.1 "iTunes", above).

A screenshot of the *iTunes* application can be seen in Figure 3.1, above. When looking at this screenshot, it is obvious that key design features and layout design is something that later generations of digital music platforms, such as online music streaming platforms, have used the *iTunes* design as a foundation when creating the user interface for their platform. To go briefly back to the 'Model T' and 'Model 3' car analogy presented earlier in this thesis, *iTunes* was perhaps not as technologically ancient as the 'Model T' compared to the 'Model 3' presented earlier in this thesis can represent *Spotify*. However, the impact of *iTunes* could still be compared to that of Ford's Model T when it comes to the importance and impact on future generations of digital music platforms.

Without *iTunes*, it is hard to imagine the online music streaming platforms of today being as good and developed as they are. Perhaps they would not have been developed at all, if not for the pioneering of the *iTunes* platform in the early 2000s.

3.6 How recommendation engines work in online music streaming services

This subchapter will focus on expanding upon types of recommendation engines that are relevant for online music streaming services and going into detail about how they function within *Spotify*. There will also be comparisons between the way recommendation engines work in *Spotify* and similar services such as *Tidal* and *Apple Music*. The focus of this part will be to understand recommendation engine types such as collaborative filtering and correlation engines within the context of online music streaming services and understand the goals of the algorithms behind them.

3.6.1 Personalized vs non-personalized, and algorithmic vs design-based

Popular online music streaming services such as *Spotify* has numerous ways to recommend content to their users. Due to this, it is arguably essential in this thesis to distinguish between **personalized** recommendations, **non-personalized** recommendations, **algorithmic,** and **design-based** recommendations. These four different categories of recommendations have not been mentioned in the text above to create a wall between the different types of recommendations, which in most instances will have some overlap between them anyways, but as a way of highlighting the key differences between how they function. Since the focus of this thesis is at its core, a split between the impact of online recommendations engines and application design on user behavior.

The use of predefined categories, which to some extent puts the recommendation system in question in a category that either leans towards online recommendation engines or the application design aspect, can help avoid confusion when discussing different types of recommendations.

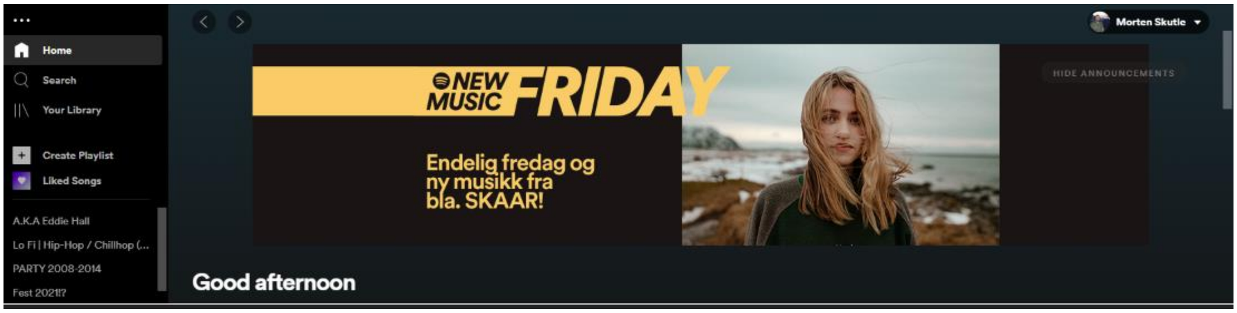
One might argue that distinguishing between different operating ways can also help clarify which types of recommendation systems have the most emphasis and impact within an online music streaming platform. There will be an attempt to define the four different types of recommendations prevalent within *Spotify*.

Personalized recommendations can be defined as recommendations which are unique to every single user of the platform. **Personalized** recommendations can be achieved by using user-specific data to make recommendations based on past user behavior on the platform and using 'neighborhood users', which are users with similar tastes and patterns, and using the data from similar users to create recommendations. Personalized recommendations are also under algorithmic recommendations since personalized recommendations depend on user data to create personalized recommendations.

An example of personalized recommendations within *Spotify* could be the 'Discover Weekly' playlist. Schrage (2020) describes 'Discover Weekly' as *Spotify'*s premier recommender system. "Each Monday, over one hundred million customers receive a customized mixtape of thirty songs they'd likely never heard before but were probabilistically likely to love. Spotify's Discover Weekly service makes an incisive case study in how rethinking recommendation and assembling algorithms profoundly changes people's path to novelty." (Schrage 2020, p. 179). *Spotify*'s 'Discover Weekly' service will be thoroughly discussed in later chapters and is one of, if not the most popular way in which *Spotify* users discover new music today. Its impact as a recommendation system is hard to understate within this thesis due to its impact on how users discover new music within the platform.

Non-personalized recommendations can be defined as recommendations that are not unique to a single user but rather an attempt at nudging users towards content recommended to them based on geolocation, popularity, and other types of attributes that are not unique to singular users. Non-personalized recommendations could arguably fall under the algorithmic and design-based recommendation category since non-personalized recommendations could be based on either algorithmic or design-based recommendations or a hybrid between them.

One could argue that non-personalized recommendations are most efficient in online music streaming services when they are utilized as a hybrid between the algorithmic and design-based recommendations due to the somewhat wide-net method, contrary to personalized recommendations. The algorithmic part of a non-personalized recommendation could be the usage of data such as geolocation. In contrast, the design-based part could be a commercial within the app or a suggestion on the ‘home’ screen in the app. Figure 3.2 on the bottom of this page illustrates this example, the mix between data-driven and design-driven recommendations.



(Figure 3.2 “New music Friday”, above)

However, one of the potential problems with non-personalized recommendations is that they in many cases attempt to reach the largest possible target audience, and therefore run into the problem of making average or below average recommendations to a larger audience, compared to how personalized recommendations are aspiring to create great, and different recommendations to every single user. Average or below-average recommendations could be better than no recommendations, primarily when said recommendations serve a purpose besides being a recommendation. For example, when looking at playlists generated by popularity such as ‘Top 50 – Norway’, ‘Top Songs – Global’, or ‘Viral 50 – Norway’, it is hard to say that Spotify generates these playlists only recommendations.

Playlists like those mentioned in the text above is arguably a digitalized and modernized way of music curation, which stems from the pre-internet analogue music curators such as for example radio DJs, record stores, and the old school type of hit-lists such as ‘Billboard Hot 100’ in the US, or ‘VG-Lista’ in Norway. From a cultural standpoint it could be beneficial from both a commercial standpoint and for normal users. For commercial interests, one could argue that following popular culture and trends within the current most popular music could be beneficial when it comes to staying relevant, and close with their target audiences.

Imagine a prominent video game developer or energy drink manufacturer using a Backstreet Boys or Britney Spears song unironically to promote a product whose target audience was born in the 2000s. The point of this example is not to cast shade on either the Backstreet Boys or Britney Spears. However, these pop-music icons' cultural impact and influence arguably had their peak in the late 1990s.

For ordinary users, these types of digital ‘hit lists’ could perhaps serve as a cultural compass for specific individuals who are not following the current pop-music trends and, therefore, wish to update themselves on what is popular at any given moment. To a certain extent, these digital ‘hitlists’ could serve as a type of anti-recommendation for users with a more niche musical taste, where the ‘hitlists’ can represent the mainstream music, which in turn can be a point of discovery for users which seeks to discover artists which they perhaps would not discover in their personalized recommendations.

3.6.2 Algorithmic recommendations

Algorithmic recommendations can be defined within this thesis as recommendations that rely on user data, together with a set of instructions as to how the information gathered from user data is to be used with the help of a computer programming language to make recommendations to users.

Professor Victoria Nash at the University of Oxfords' Internet Institute explains algorithms as “most simply as a set of instructions. So, an example of a non-internet-based algorithm would be something like a recipe for example, that gives you a set of instructions as to how to put together several ingredients to get a product, say a cake, at the other end.

Online, an algorithm is effectively the same thing. It's a set of instructions that enable a computer program to put together different sources of information and generate a result" (Nash, 2019).

Louridas (2020) describes algorithms in the context of computer science as "they [algorithms] are particular ways to solve our **problems**. These ways to solve our **problems** can be described in easy steps so that computers can execute them with amazing speed and efficiency" (Louridas 2020). While Nash (2019) has a good explanation on what an algorithm is, Louridas (2020) really defines the role of the algorithm in the context of online music streaming services.

With hundreds of thousands of new songs entering *Spotify'*s platform every single week, recommendation engines are an essential feature for both keeping users on the platform, as well as nudging users towards content which are both new to them, and perhaps also new to the platform.

3.6.3 'Discover Weekly'

*Spotify'*s 'Discovery Weekly' is perhaps one of the best examples of a form of algorithmic recommendations within the *Spotify* platform. Schrage (2020) argues that 'Discovery Weekly is *Spotify'*s premier recommender system (Schrage 2020, p. 179), while *Spotify* engineer Edward Newett describes 'Discover Weekly' as "it's as if my secret music twin put it together"

(Schrage 2020, p. 185). Arguably very much as part of the **personalized** recommendation side and an algorithmic recommendation, 'Discover Weekly' is interesting on many different levels. It utilizes a hybrid of many different types of algorithms and recommendation engines to give the user the most accurate discovery experience possible. It could, therefore, perhaps be viewed as the flagship recommendation system within *Spotify*.

According to Schrage (2020), 'Discover Weekly's algorithmic ensemble consists of five types of recommendation engines, which works together to create the weekly recommendation of 'Discover Weekly'. There will now be an attempt to describe these five types of recommendation engines.

1. Collaborative filtering algorithm, or ‘nearest neighbor’ type of recommendation. Collaborative filtering works by finding users who are similar to each other based on listening history and making recommendations based on unexplored content which users with similar listening history have explored. In the context of online music recommendations, *RINGO* was arguably the first one to use collaborative filtering.

2. Natural language processing techniques which mathematically represent implicit relationships, associations, and co-occurrences between words. They analyze playlists as if they were paragraphs and treat each song title in the playlist as if it were an individual word.

3. Outlier/anomaly detection. By definition outliers are extreme values that dramatically deviate from other observations. Outlier detection determines if a particular song is part of a normal behavior pattern or not. More on outlier/anomaly detection in ‘The Frank Sinatra experiment’ section in the next pages.

4. Deep learning/convolutional neural network (CNN) that process the acoustics, the spectrograms of songs, to identify underlying similarities in acoustic patterns. “Spotify uses a type of acoustic analysis software to classify music based on various sonic factors. For example, the algorithm takes into account key, tempo and more culturally abstract categories such as ‘danceability’ or in which degree the song fits into the use categories of ‘training’ or ‘partying’” (Kiberg 2019).

5. Finally and perhaps most obviously, how much the user liked or listened to the songs in the previous week’s ‘Discover Weekly’ playlist.

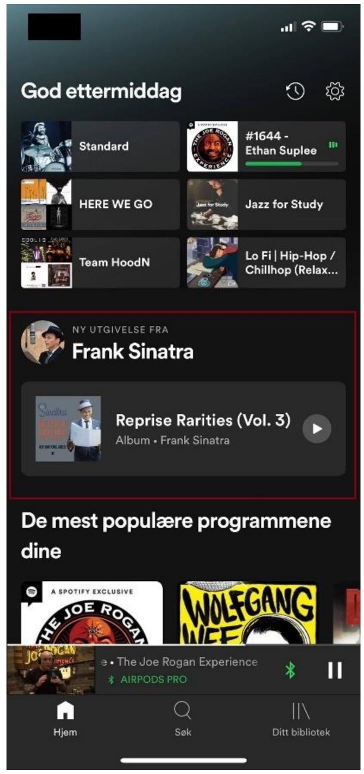
3.6.4 The Frank Sinatra Experiment

I tried to challenge this method of outlier detection within *Spotify*'s 'Discover Weekly' by conducting a small experiment while in the middle of writing this thesis. While this small experiment could by no means meet scientific research standards, as my *Spotify* account is filled with user data from 2009 to 2022, I thought it could be interesting to see if I were able to fool the algorithms to a certain extent. My procedure for this little experiment was quite simple, I only listened to Frank Sinatra for two consecutive weeks on *Spotify*.

The reasoning behind choosing the legendary artist Frank Sinatra as the artist for my little experiment was that his style of music and his active era as a recording artist was perhaps the furthest away from my listening habits at the time of experimenting. In hindsight, it would arguably be better to choose a composer from the classical period, such as Mozart or Beethoven, since these legendary composers are even further away from my music listening history.

However, the result was still quite enjoyable. It seems like the 'Discover Weekly' outlier/anomaly detection algorithm worked quite well since it did not include a single song that can be related to Frank Sinatra's music in the different criteria; the era of song/album creation, stylistic resemblance, or 'Fans also like' artists such as Bobby Darin, Dean Martin, Nat King Cole or Sammy Davis Jr. Perhaps if the experiment were conducted in a manner in which Frank Sinatra's music was, for example, sixty or seventy percent of the music played on *Spotify* throughout the experiment, contrary to a hundred percent of the music played. Alternatively, if the focus were shifted from one artist constantly streaming for two weeks to a collection of artists that share similarities in the criteria mentioned in the text above, it would have impacted the 'Discover Weekly' recommendation algorithm.

One could argue that the experiment was not a complete failure since it prompted *Spotify* to make **design-based** recommendations to me based on me listening exclusively to Frank Sinatra for a while. As shown in the red box in Figure 3.2 below, the Frank Sinatra experiment could perhaps have triggered a recommendation outside of the 'Discover Weekly' sphere to a certain extent.



(Figure 3.2, "Frank Sinatra", above)

3.6.5 Design-based recommendations

Design-based recommendations can be defined as recommendations that mainly emphasize user interface and user experience interactions within a web page/site or an app such as *Spotify*.

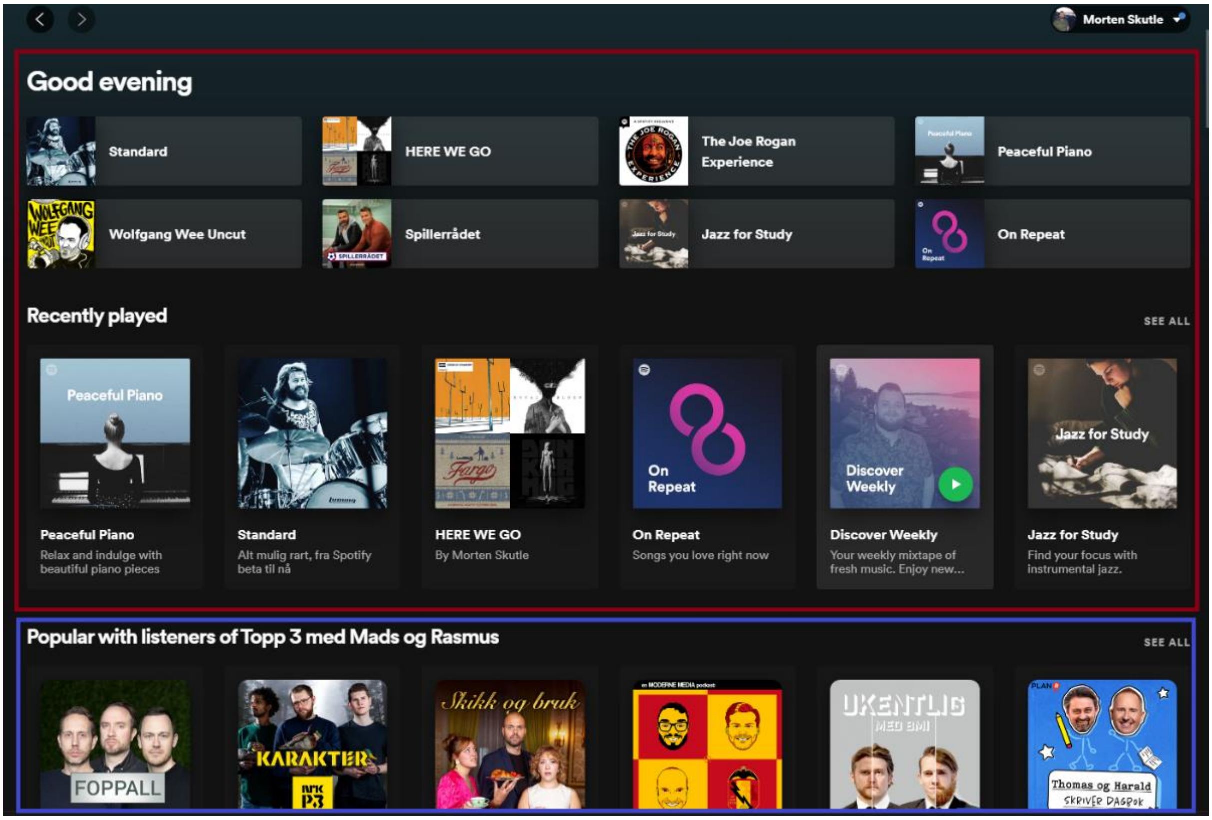
One might argue that design-based recommendations are an extension of algorithm-based recommendations or are even not possible without the presence of user data to work on. However, the yin-yang-like balance between algorithmic and design-based recommendations initially sparked the interest behind this master's thesis, and thus the relationship between the two main types of recommendations most prevalent in online music streaming services such as *Spotify*.

One could say that algorithmic recommendations are recommendation engines. Design-based recommendations are how the user is pushed, nudged, or to a certain extent, forced towards content created by algorithmic recommendations and, therefore, recommendation engines.

The link between algorithmic and design-based recommendations are crucial for either one of them to be able to be able to connect with users. To make a cheesy comparison to a more offline real-life situation, lets imagine that you are walking around in the city, and you are suddenly feeling hungry. The big green neon signs of a 7-Eleven kiosk, or the big yellow glowing M sign of McDonalds are towering high above the ground. These signs can be compared to design-based recommendations in an online music streaming service, in the way that they are guiding you towards a product or an experience.

The neon signs are not making you eat that shady bacon sausage or that dry hamburger, but they are making you, the potential customer, or user, aware of the availability of the products. Much like opening *Spotify* to instantly find on the 'Home' screen to find a doubled-up section of 'Recently played' playlists and podcasts as can be seen in the red square in the figure in the page below, as well as collaborative filtering recommendation towards podcasts which are 'Popular with listeners of' a podcast which one has recently listened to, in the blue square in Figure 3.3 in the page below.

Neon signs are replaced by incredibly easily accessible content, cleverly placed by the user experience/user interface team at *Spotify*, to get users instantly engaged in the recommended content.



(Figure 3.3 “Design-based recommendations”, above)

3.6.6 The Blackboxing of algorithmic recommendations

One of the most positive features of design-based recommendations is that they are visible to all platform users. Even though some of the intentions behind some of them are perhaps more questionable than others, visibility is critical. The visibility of design-based recommendations stands in stark contrast to the mysterious workings of algorithmic recommendations, which the average user perhaps does not understand beyond the basic concept of user data. Even for someone like myself who have spent over a year attempting to gain a deeper understanding of recommendation algorithms, it comes to a point where the mathematics and equations of an algorithms turns into a mystery.

The more mysterious the technology behind something that arguably to a large extent has the power to have an impact of the culture, and cultural development of millions of music listeners on a large online music streaming service such as *Spotify* through recommendations, the more importance it should be allocated through theoretical framework as well as speculations. In the context of the complexity of algorithmic recommendations and the issues associated with this complexity, the term 'Blackboxing' coined by Bruno Latour is highly applicable.

"Blackboxing is the way scientific and technical work is made invisible by its own success. When a machine runs efficiently, when a matter of fact is settled, one need focus only on its inputs and outputs and not on its internal complexity. Thus, paradoxically, the more science and technology succeed, the more opaque and obscure they become" (Latour 1999).

The concept of 'Blackboxing' is something that could be viewed as problematic and could potentially bring with it conflicts of interests. Especially when considering that two major record companies, Sony Music Entertainment and Universal Music Group, continue to jointly own between six percent and seven percent of *Spotify* (Ingham 2020).

Even though between six and seven percent cannot by any means be described as a controlling interest in a company, just the fact that major record labels hold ownership in an online music streaming service such as *Spotify,* opens the possibility of preferential treatment for these major record labels within the Blackbox of the algorithmic recommendations in services such as 'Discover Weekly' and others like it. Even though five key algorithms in *Spotify*s 'Discover Weekly' have been detailed in the paragraphs about the feature, Schrage (2020) does not mention if these five algorithms are equally valued when it comes to making recommendations, and it is not explicitly mentioned that there are not more ingredients of 'Discover Weekly's recommendation engines beyond these five mentioned algorithms.

Spotify is by no means alone when it comes to the potential conflict of interest between an online music streaming service and record labels or artists. *Spotify* competitor and major online music streaming service *TIDAL* has until recently been under the majority ownership of the famous American hip hop artist Jay-Z and is still co-owned by superstar artists such as Beyoncé, Madonna, Rihanna, Coldplay, and Daft Punk (Sweney 2021). Good intentions or not, ownership by artists and record labels in online music streaming services can be problematic when the recommendation engines are not hundred percent transparent.

4. Analysis of Spotify

4.1 What is *Spotify?*

According to its own website, *Spotify* (2022) describes itself as: “a digital music, podcast, and video service that gives you access to millions of songs and other content from creators all over the world. Basic functions such as playing music are totally free, but you can also choose to upgrade to Spotify premium.” (Spotify 2022). However, I would argue that *Spotify* is much more than it describes itself to be.

Founded in Sweden, in 2006 by Daniel Ek and Martin Lorentzon, and launched in 2008, *Spotify* has become that biggest online music streaming service in the world. As per Q1 2021, “*Spotify* has a marked share of 32%, with 406 million monthly active users, including 180 million premium subscribers and 226 million ad-supported (i.e., free) listeners.” (Götting 2022).

4.1.1 Cultural power and influence

Being the biggest online music streaming service in the world puts *Spotify* in a unique position of cultural power and influence. Kiberg (2019) argues that *Spotify* have become one of the culture’s leading music distributors, which in interaction with competing services and new technology gradually changes the way we interact with and are presented with music. In addition to traditional editorial recommendations (where professional editors select and highlight specific artists and songs), these platforms are operated algorithmically – where mathematical formulas, supported by large amounts of data and statistics, are able to recognize and identify relevant content to serve users, often made visible through various types of public and personal recommendation lists.

I would frame Kiberg's (2019) argument towards *Spotify* being one of the culture’s leading music distributors in a way that represents all the distribution links it has replaced through its massive growth into the most powerful music consumption platform in the world. *Spotify* has in many ways replaced or became a better alternative to:

traditional FM/AM radio, record players/CD players/mp3 players, hitlists such as ‘Billboard Top 100’ or ‘VG-Lista’, the cool older cousin or sibling which can guide you to new music, and the knowledgeable music enthusiast at your local record shop. All this, through becoming an easy-to-use online platform, which offers good recommendations to its users.

4.1.2 Amateurization and democratization

An argument can also be made that online music streaming services such as *Spotify*, in combination with increased availability of digital audio workstation software, which makes almost anyone who wants to create music able to do so, with the help of a laptop and some software, has to a large degree helped to ameteurize and democratize the music production process. The democratization and amateurization of the music production and distribution process have led to a massive volume problem, which puts the need for good recommendation engines within online music streaming platforms such as *Spotify* at a very high priority.

Wee (2022) explains the process and effect of the democratization and amateurization of the music production and distribution process as an effect of the digitalization of the music industry. “Everyone can now create music, and perhaps one of the reasons as to why we seem to think that ‘music was better before’ (1960s-early 2000s) was due to the natural filters and hierarchies which were in place due to the costs of production, and power of the record companies”. (Wee, 2022). Due to the high cost of producing and distributing music in the analogue era, the record companies which paid for said producing and distribution of music served a role as an industry gatekeeper. The ‘bad’ artists, bands, and songwriters were filtered out during the process. The bad product was rarely recorded and/or released.

However, today there is little gatekeeping due to the availability of music production software, and the availability of music distribution directly to the online music streaming services. This has led to a massive volume problem, with almost fifty thousand songs being released on *Spotify* every single day (Wee 2022). With the massive number of songs being released on *Spotify* every single day, the pressure of the recommendation engines of the platform to perform, increases.

4.1.3 Analysis of hardware platforms and purpose

To fully understand the effects and intentions of an online music streaming service such as *Spotify*, one could argue that a thorough analysis of the platform is perhaps one of the essential methods to achieve this understanding. The different parts of the analysis will be aimed at both understanding the effects and intentions of *Spotify* and looking at how those effects, intentions, and design methods could help answer some of the research questions of this thesis.

The analysis of *Spotify* is within the context of this thesis perhaps one of the most important sources to arguments, information and enlightenment, and will therefore be one of the largest chapters in this thesis.

The analysis will be divided into two sections: descriptive analysis, and design analysis. There will also be an entire chapter about the surveys in which I created to gather more information about user experience and behavior of *Spotify* users. An analysis of this survey and its findings will be featured in this chapter. These sections have been chosen due to the fact that they all contribute towards answering, either partly or perhaps fully, some of the research questions of this thesis, as well as providing any reader of this thesis a good enough understanding the analysis target, *Spotify*.

The hardware platforms of which *Spotify* will be analyzed through will be computer[desktop/laptop] and mobile. The data and images/figures provided on the computer section will be done on my personal desktop computer, running on Windows 10 64-bit operating system. The data, images, and figures for the mobile section will be done on a Huawei P30 lite, running on Android 10 OS EMUI 10.0.0.275 operating system, as well as on an iPhone 12, running on iOS 15.3.1.

4.1.4 Disclaimer about changes and updates

Throughout the writing process of this thesis from 2020 to 2022, the *Spotify* software has undergone some updates to its design. The changes are largely cosmetic and does not impact any part of the analysis of *Spotify*. The reasoning behind this little disclaimer, is so that there is no confusion from the reader of this thesis when the figures which are referred to in the following chapters are slightly graphically different from each other, even though they are taken from similar hardware platform.

The thought of comparing the 'old' *Spotify* software design to the 'new' in this chapter has been considered, however I would argue that it does not have any relevance to answering any of the research questions of this thesis. A such head-to-head comparison from 'old' to 'new' is interesting from a design perspective, however the relevancy to this thesis is not strong enough to warrant a comparison of this.

4.2 Descriptive analysis

The purpose of a descriptive analysis of *Spotify*, is to give the readers of this thesis an introduction to the functions, aesthetics, layout, and perhaps intentions of the *Spotify* platform, both on a desktop computer and a mobile hardware platform. In order to make this section of the analysis as coherent as possible, I use figures explain the user experience on the *Spotify* platform. There will also be attempted to showcase the app linearly from start to finish, from looking at the logo, to diving into the different functions. The linear approach is applied to both make the descriptive analysis as enjoyable as possible for the reader and make it as easy as possible to understand.

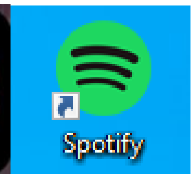
4.2.1 Aesthetics

The Cambridge dictionary defines aesthetics as “the formal study of art, especially in relation to the idea of beauty” (Cambridge University Press 2022). However, in web-design and application design, aesthetics can be more than just beauty in design elements. Thorlacius (2007) argues the importance of aesthetic in web design: “Visual communication is a reality as soon as a word is typed, a color chosen, or a text displayed on the screen, and any visual expression, whether it is intentional or not, communicates something to the visitor of the site. The Web designer can **never bypass the effects of graphic design elements**.” (Thorlacius 2007). Perhaps the aesthetic choices behind design elements in *Spotify* are more important for the *Spotify* brand, and its users, than one might think. The aesthetic choices of a platform can from a user perspective become synonymous with the platform, and thus serve as a constant reminder for the users of which platform they are currently using.

4.2.2 The Spotify logo

Before one even thinks about opening an app such as *Spotify*, consider the *Spotify* logo. It might not be as recognizable as the Coca-Cola, Apple, Facebook, or Nike logo, but one might argue that it still possesses an important attribute. A blue square with an F inside it could perhaps instantly remind one of a quite famous birthday-reminder application which doubles as a social media platform, filled with people above the age of 50 with questionable social media etiquette. Another example could be how a white mermaid looking creature with a green background could perhaps remind people of overpriced pumpkin spice lattés. The association power of just some simple symbols, with a color scheme which can stand out a little bit from the rest could arguable be quite enormous.

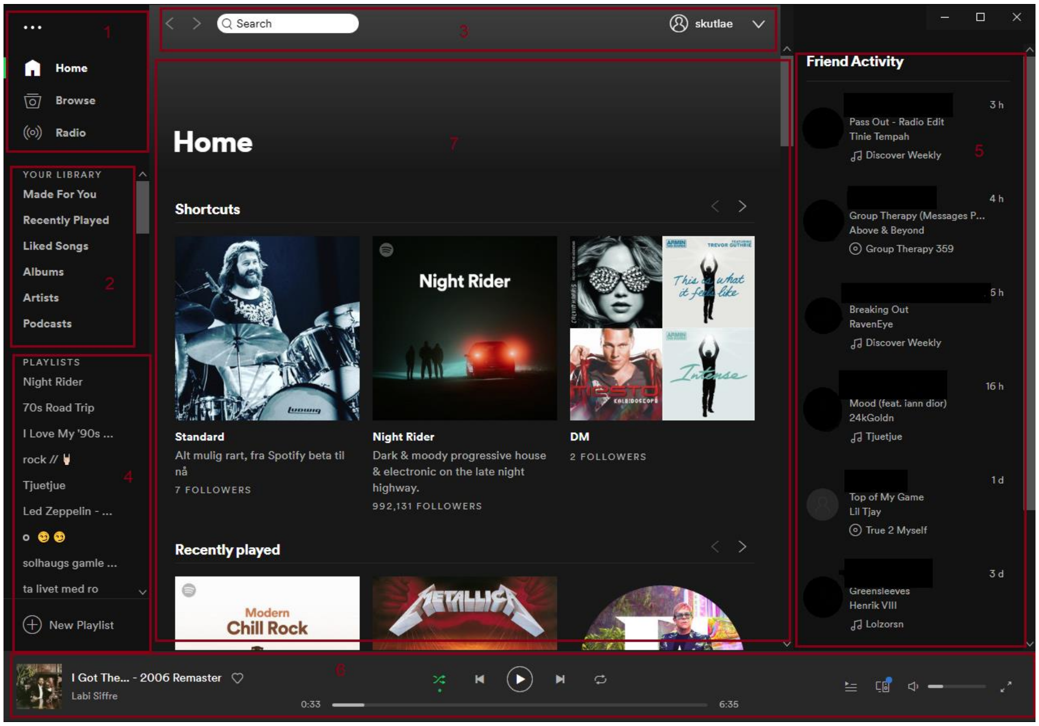
One could reasonably argue that the green and black color scheme of *Spotify* is hardly unique in the context of all the logos of all the different types of programs and apps, however in the context of a music streaming app, it has arguably achieved a degree of peculiarity.

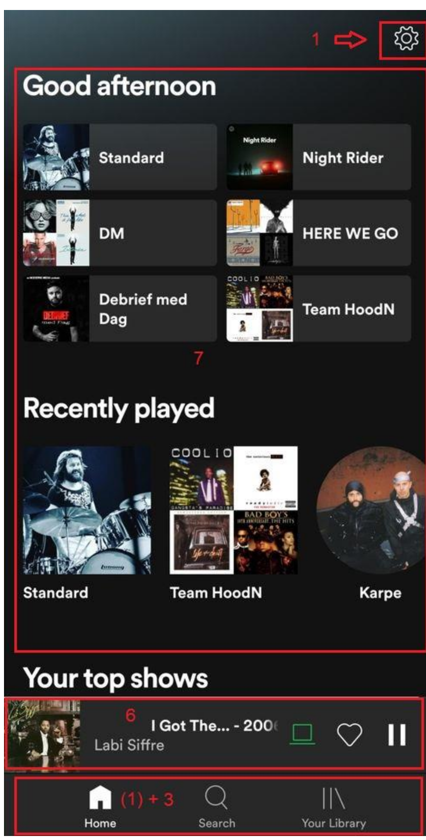
(Figure 4.0 “Spotify logo 1” above) (Figure 4.1 “Spotify logo 2” above)

Apparent at the end of the page before this one is Figures 4.0 and 4.1. Figure 4.0 shows *Spotify*’s app logo and how it is displayed on the phone, while Figure 4.1 is how *Spotify’s* logo is displayed on a computer. One might argue that logos are pretty identical. However, there are some minor differences between the logo on the two platforms. Two of the main differences between the logo of the two different platforms are that the logo on the mobile platform has a black square around the green circle, which is arguably the central part of the logo. In contrast, the logo on the computer platform is transparent outside of the central part of the logo. The other main difference between the two platforms is perhaps that the logo on the computer platform contains the text ‘Spotify’. One might argue this is done due to the much larger screen space on laptops and desktop computers than on the mobile platform.

“The color was a decision made by our founder (Daniel Ek) about 7 years ago for a simple reason: no one else was using that green. Over the years, we have earned some equity with the color […] Spotify’s brand identity has always been surprisingly sedate: black, white, and an uninspiring green for colors; an off-the-shelf font; and a little stylized sound wave as a logo” (Tischler 2015). Tischler (2015) explains that the *Spotify* logo could perhaps be interpreted as critique, however the minimalistic and perhaps surprisingly sedate black, white, and green, combined with the continuity with the font usage could also be seen as something which helps create brand identity, especially when looking at the home screen of the *Spotify* app. On the next page, there is screenshots of the home screen of the *Spotify* app, taken from a desktop computer and a mobile phone. The red numbers and red squares are edited in, to make referencing to the figures easier. The black, white, and green color theme is consistent throughout the *Spotify* platform and serves as a constant reminder for the user. This is *Spotify*.



(Figure 4.3 “Mobile HS” below) (Figure 4.2 “Desktop HS” above) (Figure 4.4 “Peaceful Piano”, below)



4.2.3 Home screens

The section below will briefly review the seven different points highlighted in Figures 4.2 and 4.3 on the page above. The focus of this section is to highlight seven key functional areas of the *Spotify* app on both computer and mobile phone platforms and provide some framework for the design and functions section later in the analysis. The seven key function areas will be revisited in this analysis's design and functions section.

On the page above, one can see the home screens from a desktop computer platform as well as a mobile phone platform. But what are 'home screens'? To briefly define 'home screens' in the context of this descriptive analysis; a home screen is the page that appears when one opens the app, in this case *Spotify*. One might argue that the brief introduction to the *Spotify* logo could perhaps be better understood when one sees the home screen of the app. The simplicity continues from the logo, into the app design.

4.2.4 Seven design points of interest

1) 'Home, Browse, Radio, and settings'

The red square which can be found on the top left of Figure 4.2, contains four main elements. The first element is the three dotted lines which when pressed opens different settings subcategories such as 'File', 'Edit', 'View' 'Playback', and 'Help'. On a mobile phone platform such as can be seen on Figure 4.3 in the page above, this section differs from the computer platform in some ways.

On the mobile phone platform, the three dotted lines are changed into a cogwheel, and the settings which is highlighted here are more directed towards using *Spotify* on the go. For example, here is a data saver mode which sets music quality to 'low', as well as the option to enable 'Car mode', and the ability connect to other apps such as navigation apps.

The second element on square number one in Figure 4.2 is the ‘Home’ button. This does also on the mobile platform, as can be seen in the bottom left in Figure 4.3. This simply brings the user back to this ‘Home screen’, if the user is on another page in the app. Home never seems to be too far away.

However, it is on the next element in square number one it really becomes interesting. Pressing the ‘Browse’ button, really opens a new world within *Spotify*. Pressing the ‘Browse’ button enables the subcategories ‘Genre & Moods’, ‘Podcasts’, ‘Charts’, ‘New Releases’, ‘Discover’, and ‘Concerts’. This section will be thoroughly covered in the design and functions analysis and will therefore not be extensively covered in this part of the descriptive analysis. One might argue that it could be worth mentioning that due to the amount of content in this section alone, that perhaps the designers of *Spotify* might be attempting to make this section the focal point of the app. More on that later in the analysis. It is also worth mentioning that this ‘Browse’ section is not available on the mobile platform.

The next and the final element in the first section is the ‘Radio’ section. When one clicks on this section, one will be recommended ten different types of user data generated ‘radio stations’, where the content is based on artists or song in which the user has listened to a lot. Within this section there is also the possibility of creating a new ‘radio station’ based on an artist/band or a song via a search function. This concludes the first of seven points of interest within the ‘home screen’ sections of *Spotify*.

2) ‘Your Library’

The second section can be found on the left side of Figure 1.2, and in the bottom right corner in figure 1.3. It contains ‘Your library’ and has the sub-sections ‘Made for you’, ‘Recently Played’, ‘Liked Songs’, ‘Albums’, ‘Artists’, and ‘Podcasts’. One might argue that this section is place where users can find content in which they have previously liked or listened to, as well as content similar to what the users have liked and/or listened to.

3 and 4) ‘Search bar, and library’

The third section is on top of Figure 4.2, and in the bottom of Figure 4.3. This section is mainly a search bar; however, it also doubles as a possibility for account settings on the desktop version of *Spotify*. The fourth section can be found on the left side on Figure 4.2 and contains all the users followed and self-created playlists. This section also has a section for creating new playlists. On the mobile platform, this section is not as omnipresent as on the computer version, however it is accessible on the mobile platform.

5) Friend Activity

In the fifth section of Figure 4.2 is the ‘Friend Activity’ section. This feature is at the time of writing this thesis one of the only features which is only available on the computer hardware platform. One can reasonable assume that this feature is not available on the mobile hardware platform due to the limited size of the screens on mobile phones, contra the big screens in which normally are used on computers. In the ‘Friend Activity’ section, one can see what music one’s friends and/or people you follow have listened to and are listening to in real time. From the ‘Friend Activity’ section, it is possible to navigate directly to the song, artist, playlist, or user profile of the friend which has listened to said song. It also states of the song is currently being played, or for example have been played 17 hours ago. The section of ‘Friend Activity’ will be revisited in the next part of this chapter. There is more to it than what we can see at the first glance.

6) ‘Media controls, and “Now Playing”’

In the sixth section in Figure 4.2 and Figure 4.3 is the control panel for the music listening in *Spotify*. On the mobile hardware platform as can be seen in Figure 4.3, it requires an action from the user to get to the same control panel as can be seen in Figure 4.2. However, basic functionality such as ‘pause’, ‘play’, and, ‘like’, are possible without navigating to another page.

The interface which appears if the *Spotify* user takes action in Figure 4.3 can be seen in Figure 4.4 on page 11. The control panel section gives the user information such as artist name, song name, song length, and controls such as play/pause, previous track, next track, shuffle play and add to favorites. As a person born in the early 1990s, these play/pause, previous/next track buttons can serve as a reminder of the analog days of the Sony Walkman and controllers for VHS machines. These control panel mechanisms are also highly similar to other music streaming services such as Apple Music and Tidal, perhaps because analog predecessors such as CD and Cassette players, various media remote controllers and so on, have carried over into the digital era.

7) Focal point

The seventh section of Figure 4.3 and Figure 4.2 is where *Spotify* wants you to pay the most attention to. It is the main course of a fancy meal, of the raisin in the sausage as we would say in Norway. It is in this section that the *Spotify* user can dive back into recently played playlists, top podcast shows, and most played playlists. Golombisky and Hagen (2016) describe sections like this as a focal point.

“The focal point can be anything really, as long as it remains the most **eye-catching piece of visual information**. […] When you look at the screen or page as a whole, one story should be dominant and function as the focal point that establishes a visual hierarchy. “ (Golombisky and Hagen 2016, p. 53).

With its thumbnail photos of recently played playlists, artists, and podcast shows, the focal point of *Spotify*’s ‘Home Screen' is inviting the user to jump back into content that the user already has spent time on. If this is done to improve the user experience within the *Spotify* application, by providing users with fast ways to jump back into the content they already have shown that they enjoyed, perhaps this is a way to keep the users engaged in the app. Keep the users listening. Keep the streaming going. Keep the money coming in. The answer to this question is probably somewhere in between ‘best user experience’ and ‘keep using our app, we want more money,’ depending on whom one should ask.

4.3 Design analysis

One of the purposes of this section of the analysis of *Spotify* is to get a better understanding of how user experience (hereinafter referred to as UX) and user interface design (hereinafter referred to as UI) is used as a tool by the creators of online music streaming platforms such as *Spotify*, to steer users towards certain types of content, as well as keep the users on the platform for as long as possible. Another purpose of this analysis section is to do a comparative analysis between *Spotify* and other online music streaming services *Tidal* and *Apple Music*, in order to get a better understanding as to what similarities there are on a surface level between these different online music streaming services, as well as key differences. The last primary purpose of this analysis section is to highlight the symbiosis between design-based recommendations and online recommendation engines.

4.3.1 User experience design vs user interface design

Describing the differences and similarities between UX and UI can sometimes be difficult, as they are in many ways intersectional. However, there are also clear distinctions when one chooses to take a closer look. Ken Norton (2018) describes the differences between UX and UI in the following way:

"At the most basic level, UI is made up of all the elements that enable someone to interact with a product or service. UX, on the other hand, is what the individual interacting with that product or service takes away from **the entire experience**". (Norton 2018)

Chinwe Obi (2018) has a great description of the differences between UX and UI, using a food order example:

"The UX consists of the user's interactions with placing their order on a company's website, their in-store experience of picking up their order, and also their satisfaction with their food. […] UI would focus on the visual design of the screens a user interacts with, such as which color to make the order button and where to place it on the page. This can also include any interfaces a user might come in contact with in-store." (Obi 2018).

To use the *Spotify* platform as an example, UI is anything a user of the platform may interact with, such as icons, buttons, menus. The surface level visual design and layout. While UX on the other hand can be described as the conceptual aspects of the design process, the big picture of the users' entire experience on the platform, from start to finish.

Since the primary purpose of this design analysis of *Spotify* is to highlight how the platform's creator is using design elements to steer users towards content, the majority of the focus will be on UX. However, I would argue that it is not possible to discuss UX without UI, and vice versa, since the two design elements are such a big part of each other's realms. The big picture narrative of UX is not possible without using UI elements. Therefore this analysis section will include a theoretical framework relevant for both UX and UI parts of the analysis object, *Spotify*..

4.3.2 Gestalt Theory

A good way of explaining UI can be used as a UX tool, as well as working towards the double-sided goal of both catering to the needs of the users of a platform, and at the same time having the main objective of having the users use the platform as much as possible, for as long as possible, in order to maximize profit from a company perspective, is to analyze a platform using four principles of Gestalt Theory. Understanding these four principles of Gestalt Theory will also help highlight the similarities between *Spotify* and other online music streaming services such as *Tidal*, and *Apple Music* later in this chapter.

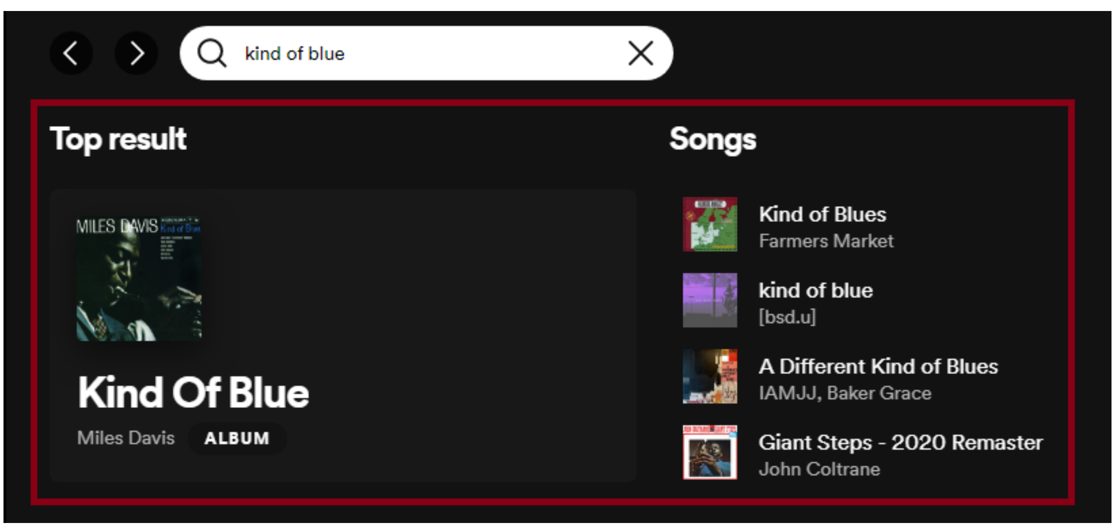
"In the early 20th century, a group of German psychologists studied the way the human brain perceives objects. *Die Professoren* discovered that the brain automatically and unconsciously simplifies, arranges and orders objects the eye see. Specific patterns of perception emerged from the research, which became the Gestalt laws. Four of these laws are of particular interest to designers" (Golumbisky and Hagen, 2016, p. 60)

The four Gestalt Theory laws of: proximity, similarity, continuity, and closure, will now be explained in the context the online music streaming service platforms. One could argue that these four Gestalt Theory laws are one of the, if not the main reason as to why the online music streaming platforms of *Spotify*, *Apple Music*, and *Tidal* are so similar in their interface designs.

4.3.3 Gestalt Theory: Proximity

According to Gestalt theory of proximity, we perceive objects close together as belonging to the same group. As shown in Figure 4.5 below, Rutledge (2019) visualizes the Gestalt theory of proximity. On Figure 4.6, one can see one example of how the theory of proximity is being applied in *Spotify*. Within the red square in Figure 4.6 we perceive two groups, 'Top result' and 'Songs'. Due to the distance between 'Top result' and 'Songs', we, as the platform user, understand that they are separate groupings from each other.

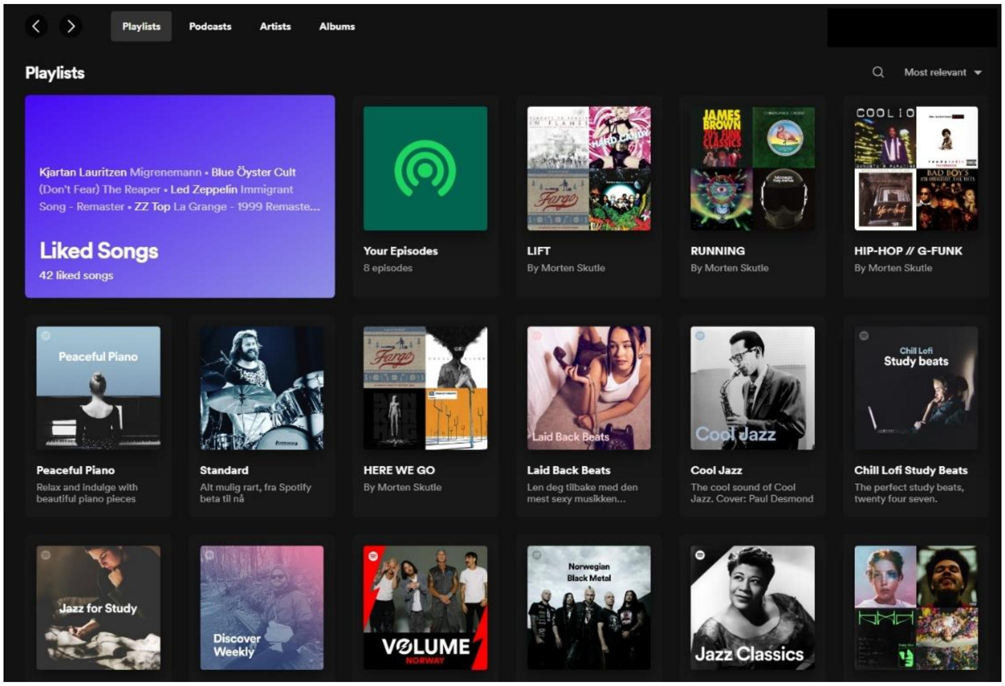
(figure 4.5 "Proximity 1", above) (figure 4.6 "Proximity 2", below)



4.3.4 Gestalt Theory: Similarity, and Continuity

Golombisky and Hagen (2016) explain the Gestalt theory of **Similarity** as this: "Our minds group things with similar properties, such as color or shape. 'Like goes with like.' […] In layout, we can use similarity to create order and organization through unity". (Golombisky and Hagen 2016, p. 62). In UI design such as on the *Spotify* platform, the Gestalt theories of **Similarity**, and **Continuity** follow each other closely.

The principle of **Continuity** states that elements that are arranged on a line or curve are perceived to be more related than elements not in line or curve. When items of similar properties are arranged in a line or curve, we can perceive them as being in strong relation to each other, if not as a direct continuation of each other. As can be seen in Figure 4.7 below, the playlists in *Spotify* are being organized by the **Similarity** and **Continuity** principles, with the thumbnails having similar shapes, fonts, and spacing, all while being arranged in a line, which can convey to the user that these similar squares are all in relation.



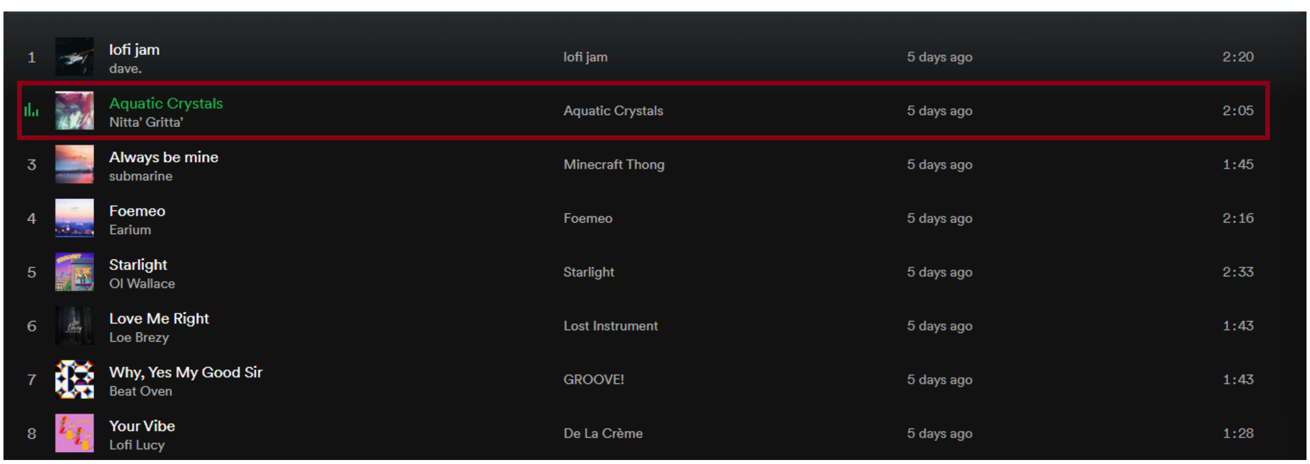
(Figure 4.7 "Similarity and continuity", above)

4.3.5 Gestalt Theory: Closure

Eduard Volianskyi explains the principle of closure as:

"[…] when we look at a complex arrangement of visual elements, we tend to look for a single recognizable pattern. In other words, when you see an image that has missing parts, your brain will fill in the blanks and make a complete image so you can still recognize the pattern." (Volianskyi 2019).

An example of the principle of closure in *Spotify* can be found in Figure 4.8 below. Figure 4.8 consists of the view of a playlist in the desktop version of *Spotify*. Closure can in this example also be a continuation of both the Similarity and the Continuity principle of Gestalt Theory, as each song is grouped together with its attributes such as 'title', 'album', 'date added' and 'time length'. Similar properties presented in a line. However, the closure aspect of Figure 1.8 can be discovered by looking at the information highlighted by the red square. The red square represents how we as the user/viewer of this information can interpret information to be in relation to each other, we create 'invisible boxes' to fill in the missing parts so that we can still recognize the pattern of composite information.



(Figure 4.8 "Closure", above)

4.3.6 Spotify, Tidal and Apple Music

Even though this thesis revolves around the most popular online streaming service *Spotify*, comparing *Spotify* to its competitors can help highlight both the differences and similarities between the different platforms, in order to get a better understanding as to how *Spotify* ended up being the biggest online music streaming platform in the world. The online music streaming services which will be compared to *Spotify* are *Tidal*, and *Apple Music*. To give some context of the size of these three different online music streaming services:

As per Q1 2021, "*Spotify* has a marked share of 32%, with 406 million monthly active users, including 180 million premium subscribers and 226 million ad-supported (i.e., free) listeners." (Dredge 2022). *Apple Music* has a marked share of 16% and is the second largest online music streaming platform. "In June 2019, Apple announced that there were 60 million people paying for an Apple Music subscription. It hasn't updated the figure publicly since then." (Dredge 2022). *Tidal* is certainly a small-timer when compared to the giants of *Spotify* and *Apple Music*. "The company has not disclosed how many people pay for its service since 2016, when it had 3 million subscribers." (Jarvey 2021).

4.3.7 Tidal and Apple Music

The main reason for choosing *Tidal* to compare to *Spotify* is to see how different a niche platform with a significant focus on HiFi sound quality, is designed, compared to the industry giant, Spotify. Other peripheral factors make *Tidal* an exciting analysis point, such as its Norwegian origins and its former majority owner Shawn Corey Carter, more commonly known as the American rapper *Jay-Z*. However, I would argue that it is important to showcase something other than the 'Top 3 most popular online streaming services', to see how up and coming platforms aim to challenge giant and established platforms through innovation and/or an intense focus on a niche aspect such as HiFi sound quality.

The reason for choosing *Apple Music* as a comparison to *Spotify*, is quite simply because *Apple Music* is the second largest online music streaming platform out there, only eclipsed by *Spotify*.

4.3.8 Welcome, “New user”

To better understand how the experience as a new user on each of these three online music streaming platforms is, I created a new account on each of the platforms. The objective of this was to attempt to understand what makes the *Spotify* user experience different from the *Tidal* and *Apple Music* user experiences.

At the account creation stage, there are differences between the three platforms which can contribute to shape the user experiences. On *Spotify*, a new user can choose between signing up with their *Facebook* or *Google* account, or to sign up with their email address. On *Tidal,* a new user can choose between signing up with their email address, *Facebook* or *Google* account, or *Apple-ID*. While on *Apple Music,* the only option available is to create an account with an *Apple-ID.* Perhaps this could be an early sign of *Apple Music* being just another overpriced product, made for the black turtleneck-wearing *Apple* tribe?

Alternatively, perhaps this is an attempt to lead the potential customer down the ‘path of least resistance’, or simply that the *Apple Music* target audience consists of users already committed to the *Apple* ecosystem. By looking around at the *Apple Music* website, it becomes more evident that *Apple Music* is made to be another piece of the *Apple* ecosystem. There are advertisements for synergy with other *Apple* products such as the *AirPods* earbuds series, the voice assistant Siri, *Apple*s CarPlay feature, direct streaming from *Apple Watch*, as well as reduced monthly prices for *Apple Music* with the purchase of an *Apple One* subscription, which includes *Apple TV+, Apple Arcade, iCloud+*, and *Apple Music.* Perhaps the lineage from *iTunes* and *iPod* is also playing a part in user retention within the Apple ecosystem. One begins to understand why users who are already deeply invested in the *Apple* ecosystem can be inclined to choose *Apple Music* over other online music streaming services.

4.3.9 The Cold-start problem

They way in which the three online music streaming platforms deals with the ‘Cold start problem’ is both interesting and quite different from each other. Zhao (2016) explains the difficulty of making recommendations without any previous data on the user, as well as traditional ways of tackling such problems in a recommendation engine environment.

“The cold-start problem, which describes **the difficulty of making recommendations when the users or the items are new,** remains a great challenge for CF [Collaborative filtering recommendations]. Traditionally, this problem is tackled by resorting to an additional interview process to establish the user (item) profile before making any recommendations.” (Zhao 2016).

One could argue that one way of somewhat dealing with the ‘cold-start problem’ could be the way in which users are prompted to create an account on *Spotify, Tidal,* or *Apple Music*, with an already existing account such as a *Facebook, Google,* or *Apple* account. This gives the online music streaming platform access to data about the user such as geolocation, email address, age, and gender. This data can then be used by the online music streaming platforms to get started on recommendations for the user. It also offers the user a really easy way of creating an account, which can help lower the barrier of entry when it comes to signing up to new online platforms.

Nodder (2013) describes this type of account creation through existing account on another platform as the ‘Path of least resistance’. “Ensure that your desired end result is on the easiest path through the process. Hide disclaimers in locations away from this path”. (Nodder 2013, p. 41). By leading the users into the ‘Path of least resistance’, one could argue that they in this instance are trading their personal data for conveniency. If it is easier, it could seem that most people just don’t care enough or think about it enough. Down the ‘Path of least resistance’ we go.

4.3.10 Solving the Cold-start problem

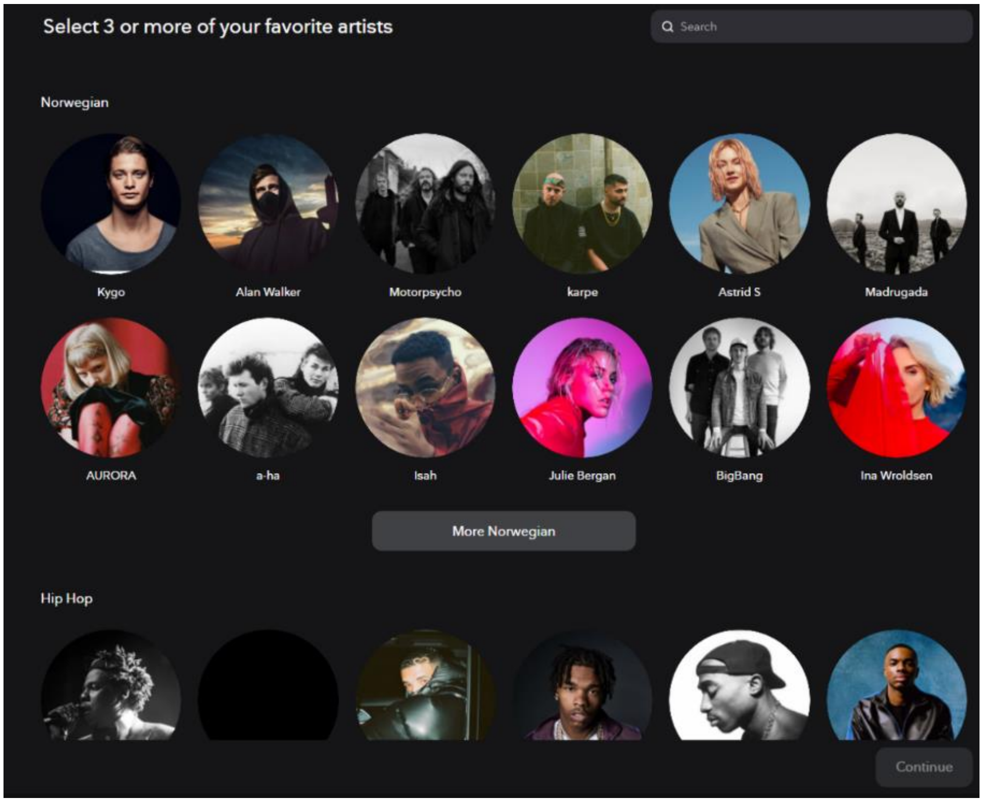
In addition to ‘Path of least resistance’ way of account creation through existing accounts on another platform, *Tidal* and *Apple Music* have some questions for their new users on the platform. As can be seen on Figure 4.9 and Figure 4.10 on the next page. *Tidal* starts by asking the user to ‘Select 3 or more of your favorite artists’, with Norwegian artists at the focal point of the screen. While *Apple Music* asks the user to ‘Choose genres you love. Your selections will inspire the recommendation that we make in Listen Now’. One could argue that these types of initial questions are there to combat the ‘Cold start problem’. These types of initial questions are also undoubtably a result of inspiration from early music recommendation systems such as the *Ringo* system in the early 1990s.

Spotify on the other hand, takes a different approach to first time users of the platform. While *Tidal* and *Apple Music* asks the users some questions about their preferred listening habits to combat the ‘Cold start problem’, *Spotify* has a more subtle approach to the introduction of their platform. As can be seen on Figure 4.11, two pages below, the new users are being thrown right into the ‘home screen’ of *Spotify*, with some modifications.

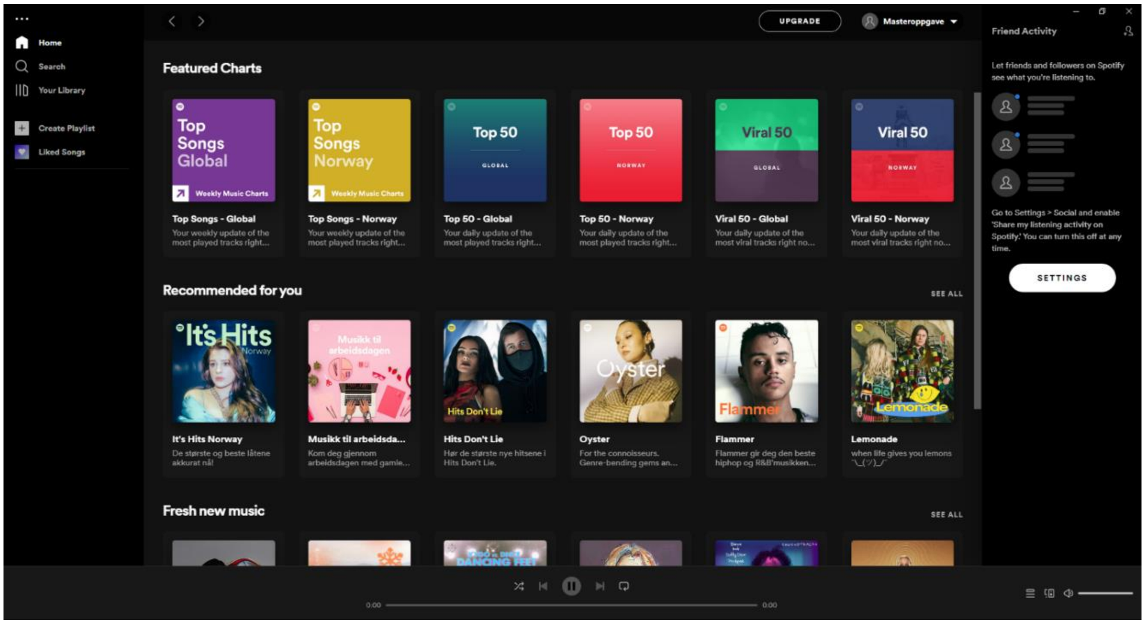
The first-time log-on ‘home screen’ is full of non-personalized recommendations, with playlists such as ‘Top 50 – Global’ and ‘Top 50 – Norway’, as well as ‘It’s Hits Norway’ and ‘Music to the workday’ playlists. The goal of these types of non-personalized recommendations at this early stage of the user experience is arguably to just give the user something to anchor on to, while the user spends enough time in on the platform for the algorithmic recommendations to be able to gather enough user data to make good recommendations.

New users are also prompted to engage in the ‘Friend Activity’ section, which is something that makes *Spotify* stand out from *Tidal* and *Apple Music*. The social media presence is there, just waiting for the users to be curious enough to test it out.

4.3.11 First time log-in screens, *Tidal, Apple Music, and Spotify*

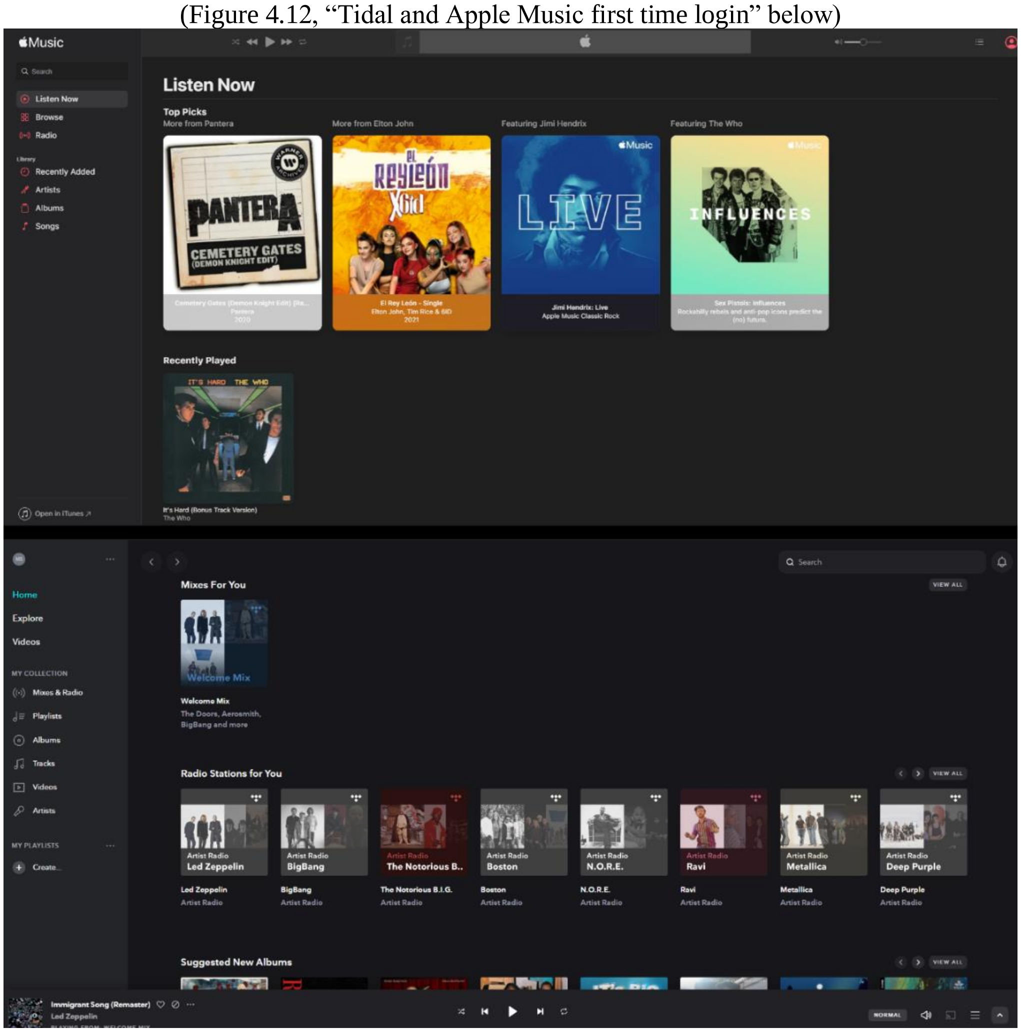


(Figure 4.9 "Tidal first login", above) (Figure 4.10 "Apple Music first login", below)



(Figure 4.11, “Spotify first time login” above)

(Figure 4.12, “Tidal and Apple Music first time login” below)



4.3.12 Platform design

When it comes to the layout design of the three online music streaming services *Spotify, Tidal*, and *Apple Music*, it is apparent that they are very similar to each other. Look at Figures 4.11 and 4.12 in the 'First-time log-in screens' section. There can be several different explanations as to why this is; one explanation could be that they all adhere to the Gestalt Theory principles of proximity, similarity, continuity, and closure, such as explained earlier in this thesis that *Spotify* is doing.

Another reasonable explanation as to why the three platforms are so similar could be connected to the fact that *Spotify* has been the biggest online music streaming platform since the late 2000s/early 2010s, and that competitors such as *Tidal* and *Apple Music* are attempting to make it as easy as possible for *Spotify* users to come over to their platform instead, without having to put an effort into learning how to navigate the platform. When new users arrive at a competing platform such as *Tidal or Apple Music,* they already know how to use it. This makes it possible for the new users to focus on the core content of the platform, rather than how to use the platform..

An argument that supports this explanation is Jacob's Law of Internet User Experience. Nielsen (2017) summarizes Jacob's Law of Internet User Experience as: "Users spend most of their time on other sites. This means that users prefer your site to work the same way as all the other sites they already know. Design for patterns for which users are accustomed" (Nielsen 2017).

Jacob's Law of Internet User Experience shows that the perceived lack of originality in platform design in the online music streaming platforms has a purpose. One could argue that the current industry leader *Spotify* have taken inspiration from earlier digital music platforms such as *iTunes.* Innovation within understandable and relatable layout design seems to be the goal, and the lineage is traceable.

4.3.13 Freemium vs subscription

One of the biggest, if not the most significant difference between how the three online music streaming platforms, *Spotify, Tidal,* and *Apple Music* operate, are the business model they use on their platforms. *Spotify* operates on a two-tiered 'freemium model', while *Tidal* and *Apple Music* operate on a 'subscription only model'.

The 'freemium model' can be briefly described as a platform divided into two categories: one free platform supported by having advertisements in between songs, advertisements on the user interface itself, and one paid subscription platform. An example of an advertisement on the user interface can be seen in Figure 3.1, in the chapter about recommendation engines. The 'free' platform also contains limitations to the mobile platform, such as a limited number of skips available while listening to any given playlist. On the other hand, the 'premium' platform includes an ad-free music listening experience, offline/download playlist functions, and the option to stream music in higher quality.

Tidal and *Apple Music*, on the other hand, have a different approach. Since they both operate based on a 'subscription only model', the barrier of entry is somewhat raised compared to that of *Spotify*'s 'freemium' model. It is more of a commitment for the users to sign up to an online music streaming service if they are required to get out their credit card to even look around on the platform.

The pricing is the same for the entry-level subscription across the three platforms, with standard subscriptions starting at 9.99$, and student subscriptions at 4.99$. *Tidal* offers 'HiFi' and 'HiFi Plus' subscriptions to its users for 9.99$ and 19.99$. The focus of *Tidal* is to deliver the highest quality audio format and therefore cater to an audiophile niche of the online music streaming audience. *On* the other hand, Apple Music solidifies itself as a musical extension of the *Apple* ecosystem, with its bundle-subscription *Apple One and* a normal subscription available. *Apple Music* also serves as Apple's descendant of *iTunes*, and through historical importance and 'path of least resistance,' probably has retained many users from the *iTunes* days.

4.4 Design impact on recommendation engines

Another exciting aspect of *Spotify*'s 'freemium' business model is how it can be an example of a feature that can lead its users towards non-personalized recommendations. An example of this could be ads for popular new album releases by significant artists in between songs or 'banner' ads for popular content, which Spotify pushes toward users. While on track to leading the users toward the non-personalized recommendations, the ads can also play an essential part in helping the users to avoid some of the biggest pitfalls of algorithmic recommendation engines. This is being stuck in a 'filter bubble'.

Originally coined by tech entrepreneur and activist Eli Pariser in 2011, the term 'filter bubble' refers to the results of the algorithms that dictate what we encounter online. According to Eli Pariser, those algorithms create "a **unique universe of information for each of us** […] which fundamentally alters the way we encounter ideas and information" (Burns 2019).

Because of the operation methods of algorithmic recommendations, the possibility of users either becoming trapped in a 'filter bubble' or at the very least being affected by it could be quite severe if the platform is not issuing countermeasures. For example, if a long-time *Spotify* user has a specific music taste, say that this user prefers to listen to classic rock from the 1970s and 1980s. The chance of this user being recommended something different than the classic rock from around the same era by the algorithmic recommendation engines are not too great.

This can lead to the user being stuck in a 'filter bubble', where similar recommendations are being recycled repeatedly, due to the user not being exposed to different recommendations than those created algorithmically of the user's own listening habits.

The consequences of being stuck in a 'filter bubble' could be harmful from both the perspective of the online music streaming service platform and that of the users of such platforms. From a platform perspective, getting its users stuck in filter bubbles is often the result of algorithmic recommendations not working as intended.

When algorithmic recommendations work at their absolute best in the context of an online music streaming platform, they provide the users of the said platform with fresh content based on user data. The algorithmic recommendations will be based on several different types of algorithmic recommendations as mentioned in the chapter about recommendation engines, such as collaborative filtering, natural language processing techniques, outlier/anomaly detection, deep learning/convolutional neural network techniques, and more. All these algorithmic methods of recommendation have in common: they are trying to replicate content based on the current listening habits of the individual users of a platform.

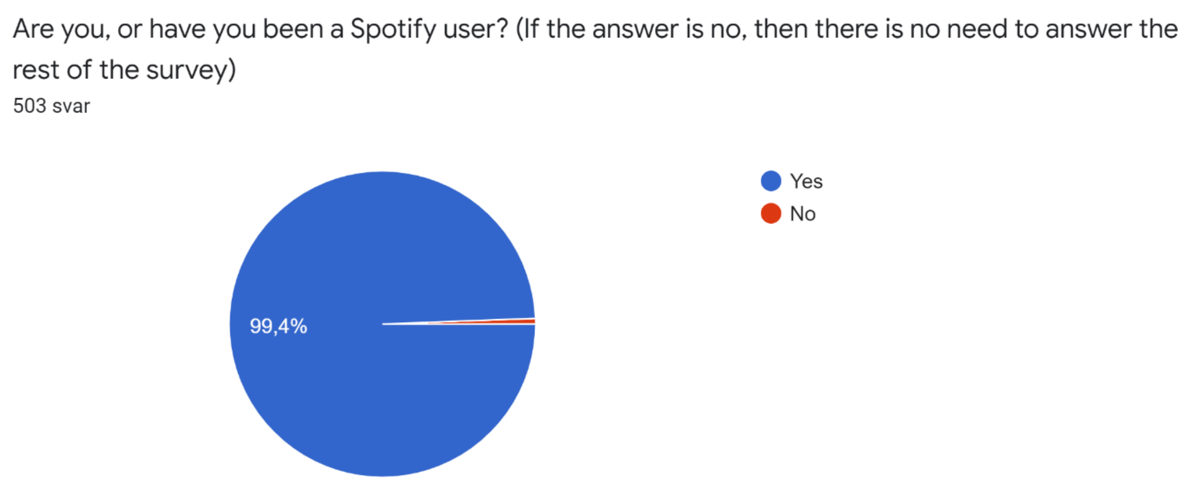
From a technical perspective, it can make sense to create algorithms to capture similarities in the music taste of users and then provide the users with 'nearest neighborhood' content again and again. However, one of the problems with making recommendations based only on user data can be that of the users ending up in filter bubbles: stuck in loops of recycled content similar to the recommendation suggested last week. Filter bubbles in themselves are perhaps not the worst part of this recycled content loop since many users arguably have a set taste preference. However, the fact that users perhaps are not aware that they are stuck in a 'filter bubble' could be a more significant issue.

This is why the connection between **design-based** and **algorithmic** recommendations is essential. The **algorithmic** recommendations can lead users towards filter bubbles and put limitations on the users' abilities to explore content. On the other hand, the **design-based** recommendations can help users break out of filter bubbles by leading users towards content not algorithmically explicitly created for individual users. Therefore, online music streaming platforms such as *Spotify*, *Tidal,* and *Apple Music* is not relying on 'one algorithm to rule them all', but rather on a mixed approach of **algorithmic** recommendations and **design-based** recommendations.

This is also why I have chosen to emphasize design elements, in a master's thesis, which is mainly about recommendation engines. In the context of online music streaming platforms, the relationship between application design and recommendation engines is symbiotic and **highly relevant to** their existence.

5. Quantitative surveys

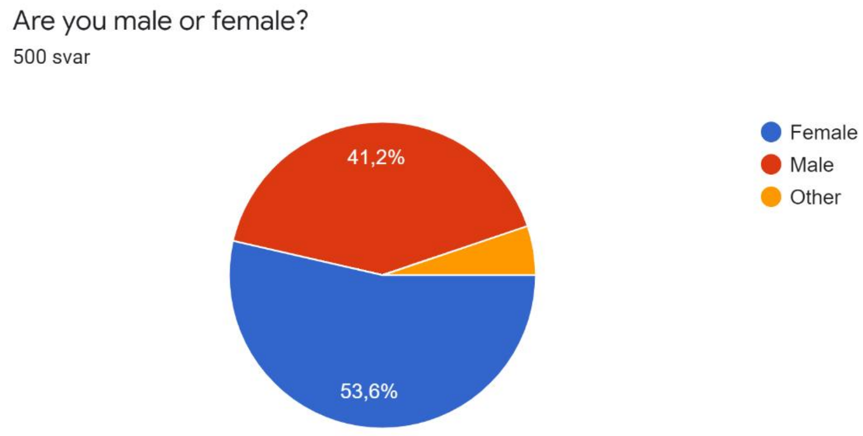
Question #1



(Figure 5.0, «Question 1», above).

The first question in surveys is a form of gatekeeping. Since the point of the surveys are to gather information from people who have used/are still using *Spotify*, the purpose of this question is to alert, and filter out any potential survey participants which have not used *Spotify* before. In the English version of the survey, 500 participants [99,4%] answered 'Yes' to the question 'Are you, or have you been a Spotify user?', while 3 [0,6%] participants answered 'No' to this question. The Norwegian survey has very similar numbers, with 465 [99,6%] participants who answered 'Yes', to 2 [0,4%] who answered 'No'.

Question #2



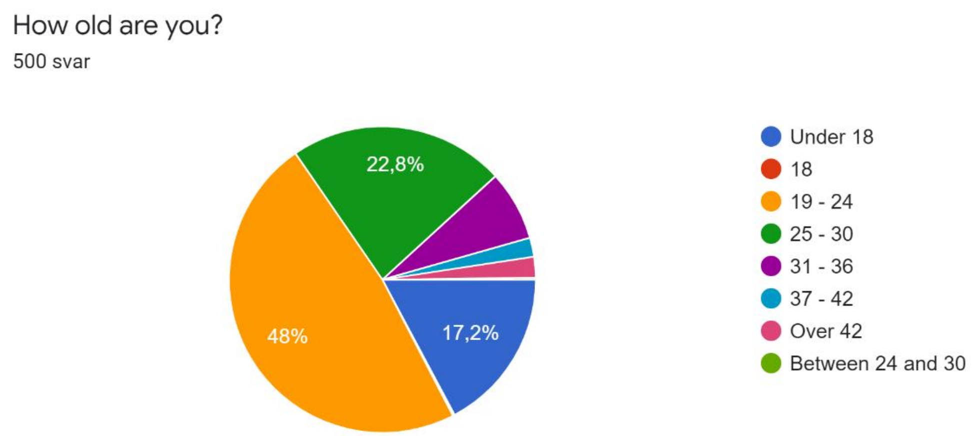
(Figure 5.1, «Question 2», above).

The survey's second question is 'Are you male or female?'—this question was intended to determine if there was a somewhat even distribution between male and female respondents. The even distribution between male and female respondents is essential because of the viability of the survey to accurately describe the behavior of the average users on the *Spotify* platform, contrary to the average male or female user. One could argue that the framing of the survey answers would have had to be different if the gender distribution was very skewed. However, since the gender distribution is so close to each other, it has not become an issue.

The English version of the survey has 500 respondents to this question, with 268 [53,6%] answering that they are 'Female', 206 [41,2%] answering that they are 'Male', and 26 [5,2%] answering that they are 'Other'. The Norwegian version of the survey has 466 respondents to this question, with 244 [52,4%] answering that they are 'Male', and 221 [47,4%] respondents answering that they are 'Female'. No one answered that they identify as 'Other', in the Norwegian version of the survey. The 'Other' answer was added a few months into the response window of the survey, after from peers in the digital culture MA, users from forums in which the survey was posted pointed out this oversight.

The male to female ratio of the survey respondents is quite similar to that of *Spotify* in total, with Hlebowitshs (2022) statistics from 2022 showing that “56% of Spotify users are male and 44% are female”.

Question #3



(Figure 5.2, «Question 3», above).

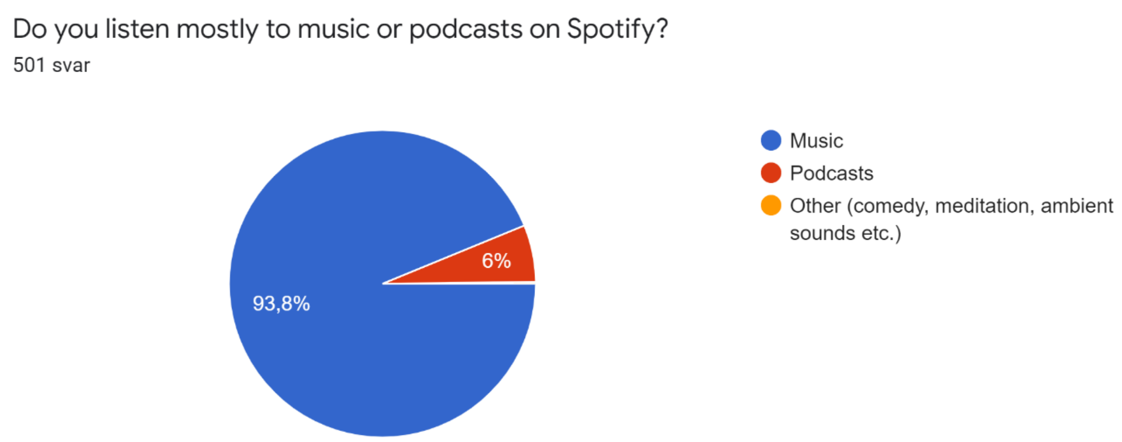
The third question of the survey is ‘How old are you?’. The reasoning behind this question was to see if there was any age group which stood out in a large majority, as well as to see if there is any big difference between the answers to the English and Norwegian versions of the survey.

The English version of the survey has 500 respondents to this question, with the three largest age groups being ’19 – 24’, with 240 [48%] respondents, ’25 – 30’, with 114 [22,8%] respondents, and ‘Under 18’, with 86 [17,2%] respondents. The Norwegian version of the survey on the other hand, has 466 respondents to this question, with the three largest age groups being ’19 – 24’, with 233 [50%] respondents, ’25 – 30’, with 132 [28,3%] respondents, and ’31 – 36’, with 33 [7,1%] respondents.

The biggest different between the English and Norwegian versions of the survey, are the third largest respondent-groups. The third largest respondent-group on the English version, ‘Under 18’, with 86 [17,2%] respondents, only had 13 [2,8%] respondents on the Norwegian version of the survey. The third largest respondent-group in Norwegian, ’31 – 36’, with 33 [7,1%] respondents, has quite similar numbers on the English version, with 37 [7,4%] responders.

One notable thing about the response to this question is that there is a potential for bias, both from the English/International and the Norwegian survey answers to this question. With the majority of the survey respondents from this question being between the age of '19 – 30', one could argue that there is a rather large possibility that the largest represented age groups in which the survey has been inflated due to responses from Reddit, and my social media platforms, which both have a majority of people around that age group. With the '19 – 24' and '25 – 30' age groups being the most prominent age groups, the results from the survey respondents can give an exciting insight into the listening habits and preferences on online music streaming platforms, as well as awareness of the effects of online recommendation engines and user experience design on young adults in their twenties.

Question #4

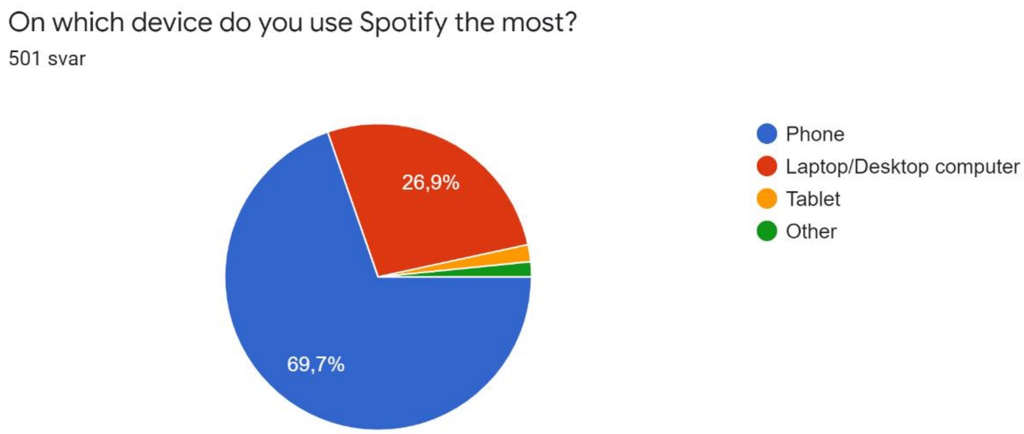


(Figure 5.3 «Question 4», above).

The fourth question of the survey is 'Do you listen mostly to music or podcasts on *Spotify*?'. This question was created to get confirmation that many of the *Spotify* users are mostly using the platform to listen to music. The English version has 501 answers to this question, which 470 respondents [93,8%] answered 'Music', and 30 [6%] respondents answered 'Podcasts'. The 'Other' category for zero respondents, both on the English and the Norwegian version of the survey.

The Norwegian version of the survey have very similar answers as the English one, with 447 respondents [96,3%] which answered ‘Music’, and 16 [3,4%] which answered ‘Podcasts’.

Question #5



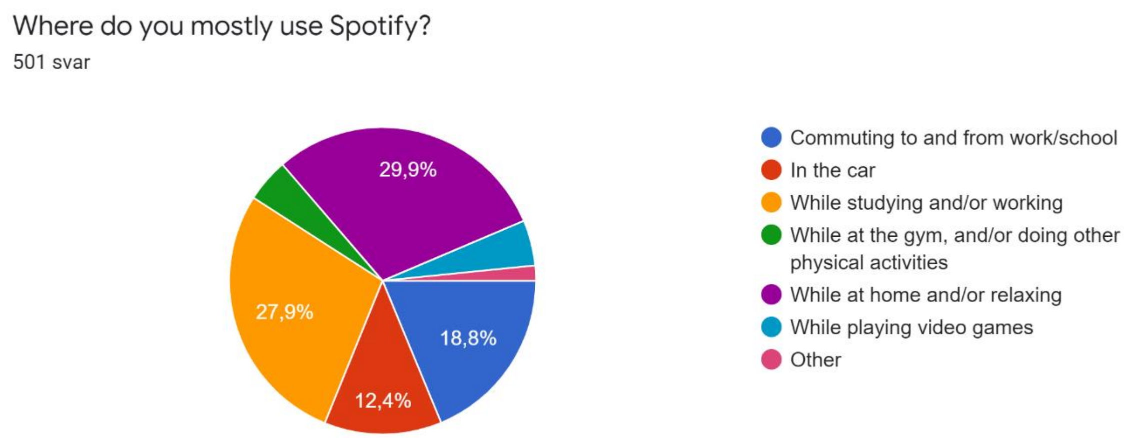
(Figure 5.4 «Question 5», above).

The fifth question of the survey is ‘On which device do you use *Spotify* the most?’. The answers from the survey respondents on this question were different than my initial hypothesis, approaching this question. My hypothesis was that it would be more of a fifty-fifty split between the ‘Phone’ and ‘Laptop/Desktop computer’ answers. However, this hypothesis was purely based on personal experiences, as and casual conversations with peers and people in my social circle.

The English version has 501 answers to this question, which 349 [69,7%] respondents answered ‘Phone’, 135 [26,9%] answered ‘Laptop/Desktop computer’, and a small percentage answered ‘Tablet’, and ‘Other’, with 9 [1,8%] and 8 [1,6%]. The Norwegian version of the survey has 464 answers to this question, which 392 [84,5%] respondents answered ‘Phone’, 65 [14%] answered ‘Laptop/Desktop computer’, and a small percentage answered ‘Tablet’, and ‘Other, with 2 [0,4%], and 5 [1,1%].

Interestingly, most of the survey respondents are using their mobile phones as their primary platform for online music streaming services. It is also interesting to see the difference between the English and Norwegian versions of the survey. The Norwegian version has almost a 15% increase in ‘Phone’ answers compared to English. Perhaps one of the reasons why the ‘Phone’ answer got a more significant response than perhaps expected, can be linked to the fact that the survey respondents are mostly in their twenties, and therefore can be more technologically leaning towards the mobile platform, than perhaps older generations are. The relationship between listening habits of those who primarily listen on mobile devices versus computers is interesting to do further research on, perhaps in another paper or thesis.

Question #6



(Figure 5.5 «Question 6», above).

The sixth question of the survey is ‘Where do you mostly use *Spotify*?’. I would argue that the importance of this survey question is to highlight if the users of the *Spotify* platform are mostly using music as a tool for productivity, such as for example the ‘While studying and/or working’ answer, or the ‘While at the gym, and/or doing other physical activities’ answer, or if the *Spotify* users are more inclined to use music as more of an enjoyment of the artform such as the ‘While at home/or relaxing’, or perhaps to a certain degree ‘Commuting to and from work/school’.

This is relevant, due to users which are primarily using music as a tool for productivity can have a greater consumption of playlists made for certain activities, such as studying, going to the gym, and so on and so forth, than users which mostly listen to music for the music itself, and not as a productivity tool. This will can then develop into form of the *Matthew Effect* in the sense of recommendations.

Bartley (2016) describes the *Matthew Effect as* «a social phenomenon often linked to the idea that **the rich get richer and the poor get poorer**. In essence, this refers to a common concept that those who already have status are often placed in situations where they gain more, and those that do not have status typically struggle to achieve more. » (Bartley 2016).

Those who already have good algorithmic recommendations, will keep getting better algorithmic recommendations, and those who are perhaps stuck in a 'filter bubble', and are receiving bad algorithmic recommendations will keep getting even worse algorithmic recommendations.

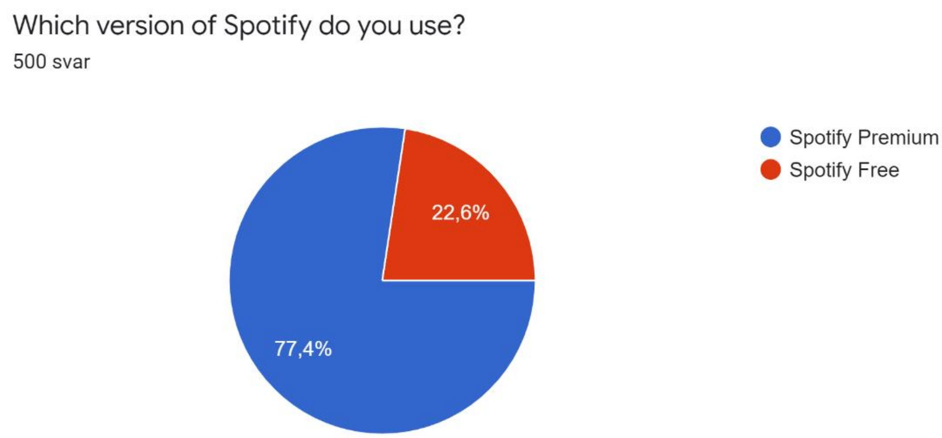
If users mostly use playlists which are constructed as being a tool for productivity, the personal recommendations could be diminished, as those types of playlists often aim to capture a certain mood. For example, a typical 'Gym' playlist can often consist of up-tempo music which are intended to hype the users up and give them energy to keep going hard at the gym, while a typical 'Study' playlist can be more of an attempt at calming the mind, with emphasis on for example 'Peaceful piano', or 'Relaxed Jazz'.

The algorithmic recommendation challenge for these types of users lie in the way music is being used as a tool for productivity, and perhaps not as a defined personal taste. Neither the English or Norwegian version of the survey showed a majority of these types of 'music as a tool for productivity' users, however I would argue that showing that *Spotify* users use the platform for different reasons, and therefore can receive different recommendations based on their user behavior is important in the context of this thesis.

The English version of this question has 501 answers, which 150 [29,9%] respondents answered, 'While at home and/or relaxing', 140 [27,9%] respondents answered, 'While studying and/or working', 94 [18,8%] respondents answered, 'Commuting to and from work/school'. The 'In the car' answer got 62 [12,4%] of the responses, while the 'While at the gym, and/or doing other physical activities', the 'While playing video games', and the 'Other' answers got 23 [4,6%], 24 [4,8%] and 8 [1,6%] responses.

The Norwegian version of the survey with, its 465 answers, on the other hand, had a different majority than the English version. With 148 [31,8%] respondents answered, 'Commuting to and from work/school', 103 [22,2%] respondents answered, 'While at home and/or relaxing', and 82 [17,6%] respondents answered, 'While studying and/or working'. 54 [11,6%] of the respondents answered, 'While at the gym, and/or doing other physical activities', 50 [10,8%] of the respondents answered, 'In the car', while the 'Other' and 'While playing video games' got 18 [3,9%] and 9 [1,9%] respondents.

Question #7



(Figure 5.6, «Question 7», above).

The seventh question of the survey is 'Which version of *Spotify* do you use?'. I would argue that the results from this survey question show the success of the *Spotify* 'freemium' business model, as discussed in the analysis chapter. Even though there is a free version of *Spotify*, almost everyone in both the English and the Norwegian version of the survey answered that they use *Spotify Premium*.

The English version of this question has 500 answers, which 387 [77,4%] respondents answered, 'Spotify Premium', and 113 [22,6%] respondents answered, 'Spotify Free'. The Norwegian version of this question has 465 answers, which 444 [95,5%] answered 'Spotify Premium', and 21 [4,5%] answered 'Spotify Free'.

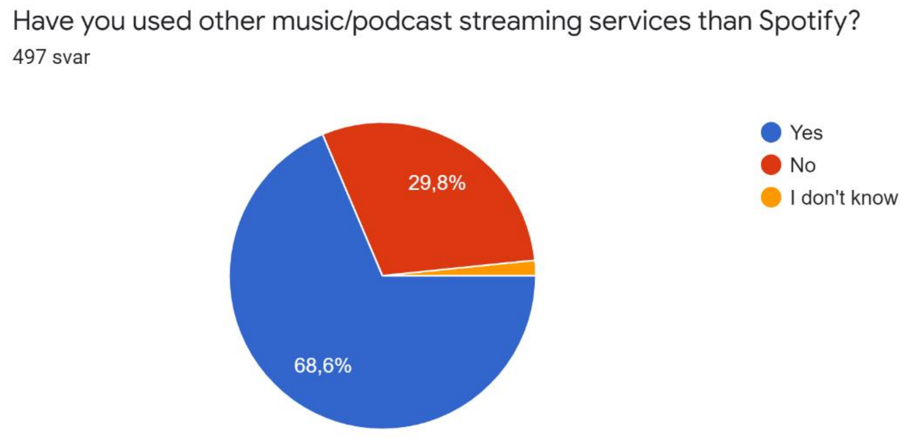
One of the reasons as to why the Norwegian survey has such high answer rate on the 'Spotify Premium' answer, with 95,5% answering that they use the paid subscription version of the online music streaming platform, compared to that of 77,4% in the English version of the survey, could boil down to the economic situation in Norway compared to many other places in the world. As one of the wealthiest countries in the world, adults living in Norway can undoubtedly afford to pay 9,99$ a month for a *Spotify Premium* subscription. For people living in less economically fortunate places around the world, paying that 9.99$ a month for an online music streaming service that already has a free version could seem like too much.

Question #8

The eight question of the survey is 'Why do you use the premium or free version of Spotify?'. Unlike the survey questions before this one which had multiple choice answers, I decided to allow short sentence answers on this question. After going through 893 answers in both the English and the Norwegian version of the survey, it is possible to conclude that most of the survey respondents are *Spotify Premium* subscribers to be able to have an ad-free music experience, as well as being able to have unlimited skips on mobile devices, and offline-availability on both the computer and the mobile hardware platforms.

The arguments for the free version of *Spotify* are few but usually consist of either the user not using the platform enough to warrant paying for it or that it is simply too expensive for them. After going through 893 survey answers to this question a few times, I can conclude that allowing short sentence answers in a quantitative survey such as this one is not the most fantastic idea. Data visualization is complex, and the time spent versus reward from longer and unique answers is not worth it.

Question #9



(Figure 5.7, «Question 9», above).

The ninth question of the survey is ‘Have you used other music/podcast streaming services than Spotify?’. I would argue that the relevancy of this survey question is connected to verifying that the majority of *Spotify* users have tried different online music streaming platforms such as *Tidal*, *Apple Music*, *Amazon Music*, and others. This verification is essential to establish something about the *Spotify* user experience that draws users back to the platform. Users are not just jumping on the bandwagon and going straight to the largest online music streaming platform.

The English version survey has 497 answers to this question, which 341 [68,6%] respondents answering ‘Yes’, to 148 [29,8%] answering ‘No’, and 8 [1,6%] answering ‘I don’t know’. The Norwegian version of the survey has somewhat similar numbers as the English version, with 463 answers to this question, which 281 [60,7%] respondents answering ‘Yes’, to 176 [38%] answering ‘No’, and 6 [1,3%] respondents answering, ‘I don’t know’.

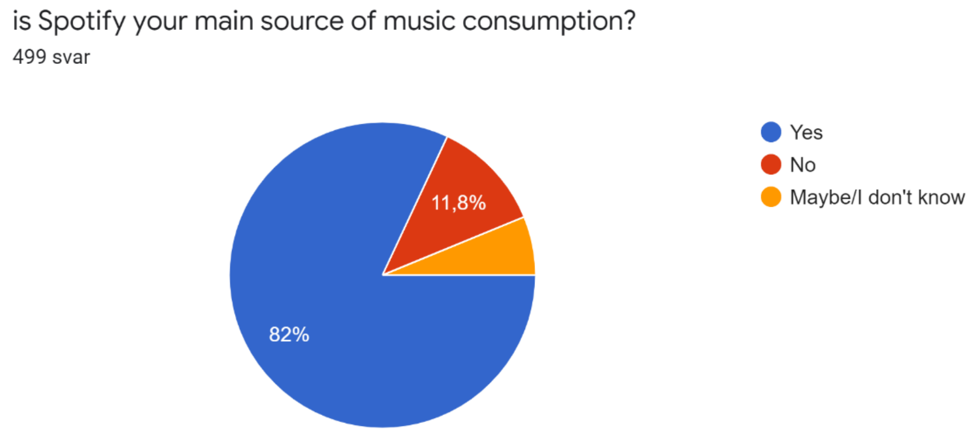
Question #10

The tenth question of this survey is ‘Why do you use Spotify over other music/podcast streaming services?’. At the time it seemed like a practical segue from the previous question of ‘Have you ever used other music/podcast streaming services than Spotify?’, however the decision was made to make this survey question a short sentence type of answer. In hindsight, just as with question number eight, I would not have made this decision again, due to the data overload and the lack of data visualization.

However, this survey question still received some important answers as to why users prefer *Spotify*. The English and Norwegian versions of the survey have 794 answers combined on this survey question, and even though there are many different types of answers to this question, some were more recurring than others. Phrases such as ‘Convenience’, ‘Easy to use’, ‘Large catalogue’, ‘Discover weekly/Good recommendations’, and ‘Been using it so long, why switch’ are recurring in the majority of the answers, in both the English and Norwegian versions of the survey.

The answers in the line of ‘Convenience’ and ‘Easy to use’ can be interpreted as an argument for *Spotify’*s smart UI and UX design, by following key design theories mentioned in the design analysis chapter, such as *Gestalt Theory* and *Jakob’s Law of Internet User Experience*, the platform can seem intuitive and easy to use even for new users of the platform. The ‘Large catalogue’ type answers can be attributed to *Spotify* being the biggest online music streaming service. If the *Spotify* platform is where everyone is, then by logic, every artist/label would want to be available on that platform in order to reach the largest possible audience. The ‘Discover weekly/Good recommendations’ answer shows that a rather large amount of *Spotify* users are preferring *Spotify* over other platforms due to their recommendation. This is key in the context of the next question of the survey.

Question #11



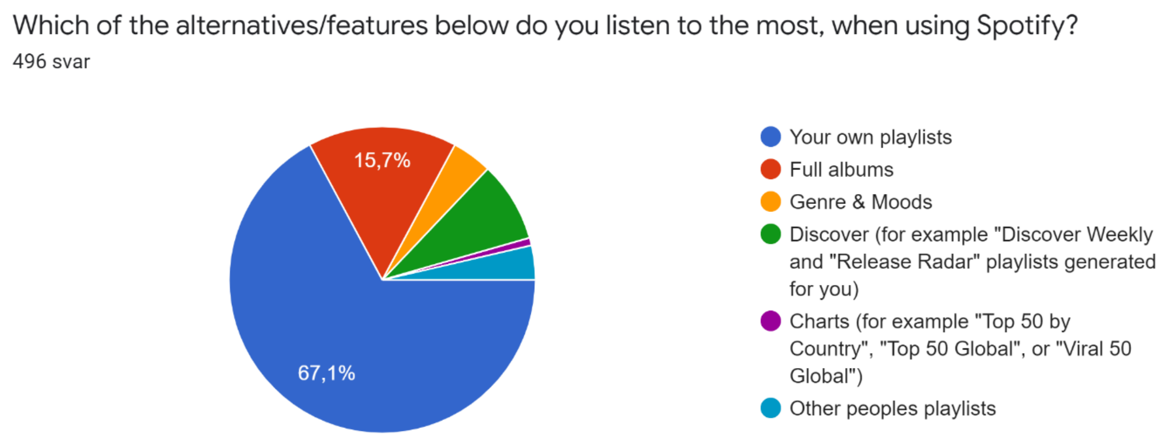
(Figure 5.8 «Question 11», above).

The eleventh question of the survey is ‘Is Spotify your main source of music consumption?’. This question is important in the context of filter bubbles, and tenth question of this survey, more precisely the fact that ‘Discover weekly/Good recommendations’ were a rather large number of answers to question number ten.

If the ‘Discover weekly/Good recommendations’ are a large reason as to why users prefer the *Spotify* platform over its competitors, combined with the fact that 409 [82%] of the 499 respondents in the English version of the survey, and 415 [89,4%] out of 464 respondents in the Norwegian version of the survey answered that *Spotify* is their main source of music consumption, the cultural influence of the *Spotify* platform becomes visible. With such a high percentage of *Spotify* users stating that the online music streaming platform is their main source of music consumption, connected with the ‘Discover weekly/Good recommendations’ being a big attraction that brings users to the platform, the risk of users falling into algorithmically created filter bubbles are arguably increased. However, the survey question does not state of *Spotify* is their **only source** of music consumption.

The influence of other music consumption platforms can at least help users realize if they are indeed fallen into an algorithmically created filter bubble.

Question #12



(Figure 5.9 «Question 12», above).

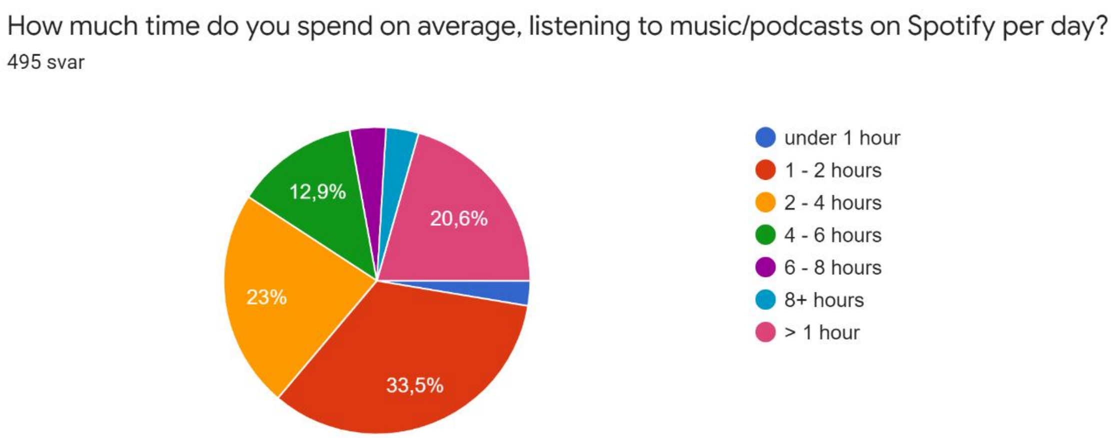
The twelfth question of the survey is 'Which of the alternatives/features below do you listen to the most, when using Spotify?'. The top three answers to this survey question are the same in both the English and Norwegian versions of the survey, with the 'Your own playlists' being the biggest with 333 [67,1%] of the respondents in the English version, and 346 [74,7%] on the Norwegian version. The second largest response to this survey question is the 'Full albums' answer, with 78 [15,7%] respondents on the English version, and 52 [11,2%] on the Norwegian version. In third place on both versions of the survey is the 'Discover (for example «Discover Weekly» and «Release Radar» playlists generated for you)', with 42 [8,5%] respondents on the English version, and 28 [6%] respondents on the Norwegian version of the survey.

One could argue that the fact that the users are spending the most time on the *Spotify* platform listening to their own playlists is hardly any surprise, however the more interesting question in the context of this thesis could be how the users find the music for their own playlists.

However, that the 'Full albums' alternative is the second largest response on both the English and Norwegian version of the survey is somewhat surprising and can show a shift in how online music streaming services facilitate music listening experiences of their users contrary to earlier forms of online music such as *iTunes*, and the times of illegal music downloading in the early 2000s, which were not album-centric per say, but more centered around popular singles and/or songs.

It is also interesting to see that the algorithmically generated ‘Discover’ answer alternative is the third-largest answer alternative in both the versions of the survey and is bigger than answer alternatives such as ‘Charts’, ‘Genres & Moods’ and ‘Other peoples playlists’. It shows that algorithmic recommendations are a large part of the users’ *Spotify* experience.

Question #13



(Figure 5.10 «Question 13», above).

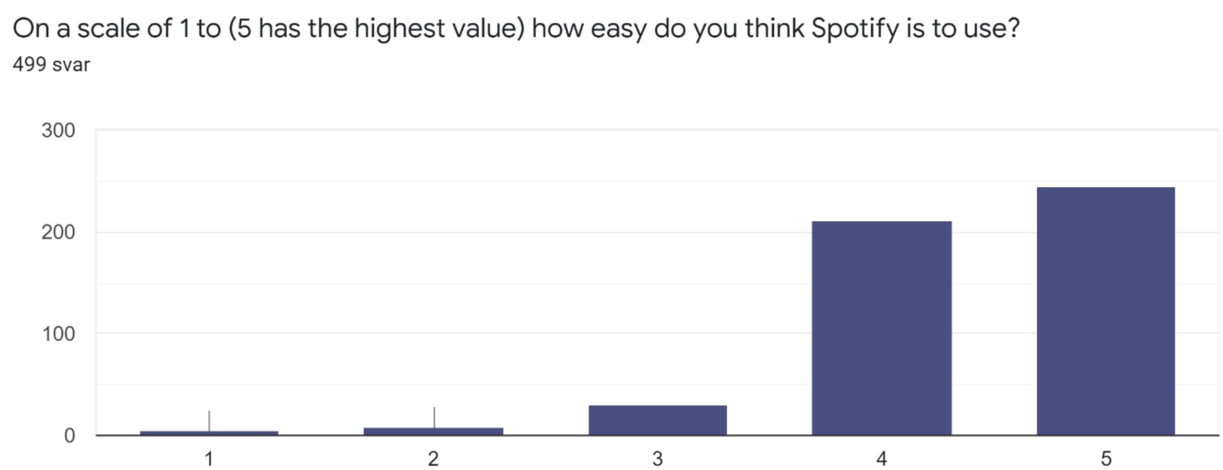
The thirteenth question of the survey is ‘How much time do you spend on average, listening to music/podcasts on Spotify per day?’. The purpose of this survey question is largely to identify if there are any significant differences between the Norwegian *Spotify* users and the international ones, which have answered the Norwegian and English versions of the survey. It is also nice to have some information about how much the survey respondents are using platform, in relation to other survey questions.

The English and Norwegian versions of the survey have the same top four answers to this question, with ‘1 – 2 hours’ being the number one answer with 166 [33,5%] respondents on the English version of the survey, and 168 [36,5%] on the Norwegian version of the survey.

The second largest answer group is the '2 – 4 hours' answer, which has 114 respondents [23%] in the English version, and 116 [25,1%] on the Norwegian version of the survey. The third largest answer group on both versions of the survey is the '> 1 hour' answer, which got 102 [20,6%] respondents on the English version, and 80 [17,3%] respondents on the Norwegian version. The '4 – 6 hours' answers got 64 [12,9%] respondents on the English version, and 49 [10,6%] respondents on the Norwegian version of the survey.

The biggest take-aways from this survey question, is arguably that the Norwegian survey respondents spend more or less a similar amount of time listening to music/podcasts on *Spotify* per day.

Question #14



(Figure 5.11 «Question 14», above).

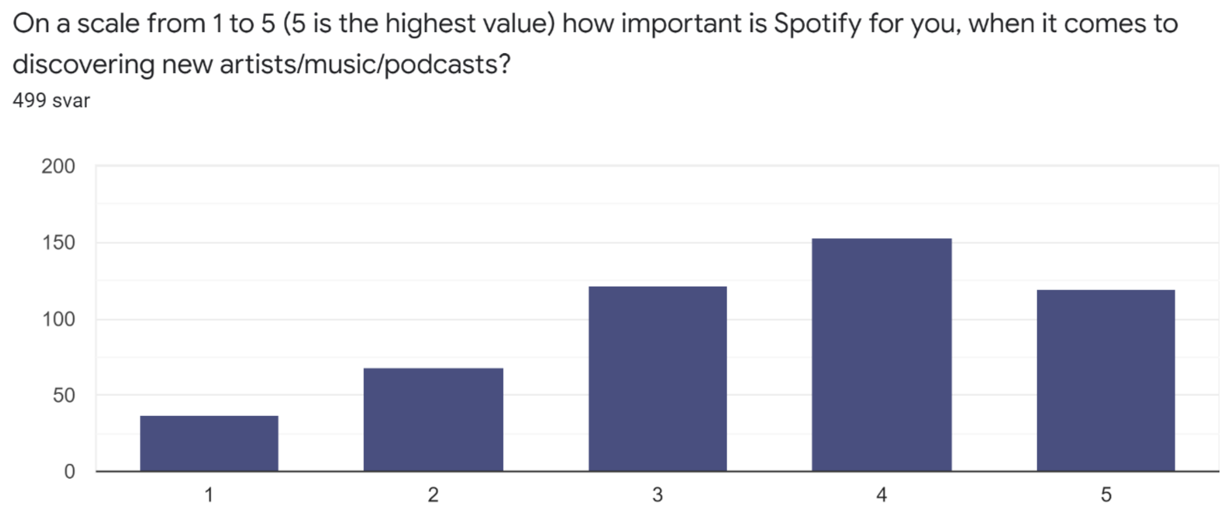
The fourteenth question of the survey is 'On a scale of 1 to 5 (5 has the highest value) how easy do you think Spotify is to use?'. Contrary to the previous questions in the survey which has contained multiple choice answer, and short sentence answers, this survey question and the next nine survey questions are gradient type questions, where the survey respondents rate a claim in the question from one to five, where five has the highest value.

One of the main purposes behind the gradient type questions is to see to which extent the survey respondents agree or disagree with certain key questions related to this thesis.

The top three answers to this survey questions are the same on the English and Norwegian version of this survey, however the distribution is somewhat different. The '5' answer got the most respondents in both versions of the survey, with 244 [48,9%] respondents in the English version, and 292 [63,3%] respondents on the Norwegian version of the survey. The '4' answer got the second most respondents, with 212 [42,5%] respondents on the English version, and 157 [31,1%] respondents on the Norwegian version of the survey. The '3' answer got the third most respondents, with 30 [6%] respondents on the English version, and 10 [2,2%] on the Norwegian version of the survey.

The results from this survey question clearly shows that both the Norwegian and international *Spotify* users are finding the platform easy to use. One could argue that this is the result of *Spotify* following good UX and UI design practices and theories on the platform, such as emphasized in the design chapter of this thesis. However, one could also argue that such design practices are to be expected from an industry leader such as *Spotify*, and that perhaps the high percentage of survey respondents answers in the high values ['4' and '5'] can also be linked to the fact that the survey respondents in this case are rather young, with more than 75% of the survey respondents in both the English and the Norwegian versions of the survey being under the age of 40.

Question #15

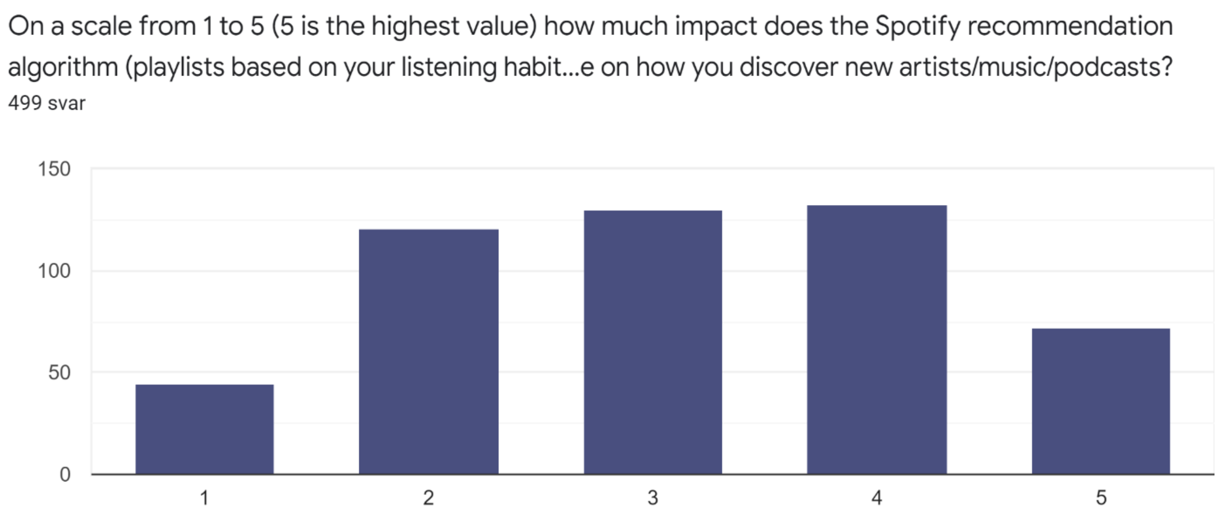


(Figure 5.12, «Question 15», above).

The fifteenth question of the survey is ‘On a scale from 1 to 5 (5 is the highest value) how important is Spotify for you, when it comes to discovering new artists/music/podcasts?’. The answers to this survey question are quite similar in both the Norwegian and the English version of the survey, with the ‘4’ answer being the biggest answer in both versions of the survey, with 153 [30,7%] respondents in the English version, and 148 [32%] respondents on the Norwegian version of the survey. The second largest answer is different on the two versions of the survey, with the ‘3’ answer being the second largest one of the English version of the survey with 122 [24,4%] respondents, and 118 [25,5%] respondents on the Norwegian version of the survey. The ‘5’ answer got the second most answers in the Norwegian version of the survey with 137 [29%] respondents, while it became the third most answered choice in the English version of the survey with 119 [23,8%] respondents.

I would argue that the survey respondents expressing that *Spotify* is important for them when it comes to discovering new artists/music/podcasts is not surprising when put in the context of other survey responses, such as in question 11 in the surveys, where 82% of the respondents in the English version of the survey, and 89,4% of the respondents in the Norwegian version of the survey, answered that *Spotify* is their main source of music consumption. However, from looking at the response to this survey question, one could think that *Spotify* has taken over as the new digital 'cool older brother' and 'hip person working at the record store.' Advice on new and cool music no longer comes from people in physical proximity but rather from our algorithmically suggested 'nearest neighbors' and algorithmic curation.

Question #16



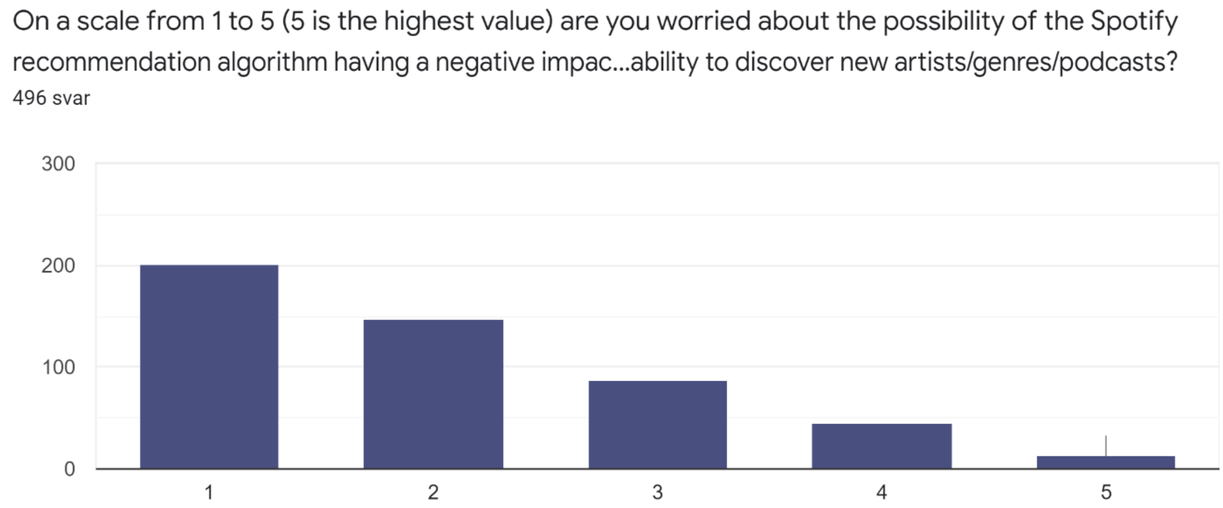
(Figure 5.13 «Question 16», above).

The sixteenth question of the survey is 'On a scale from 1 to 5 (5 is the highest value) how much impact does the Spotify recommendation algorithm (playlists based on your listening habits, and artists/songs/podcasts based on your listening habits) have on how you discover new artists/music/podcasts?'. This survey question, together with survey questions eleven, fifteen, as well 'Question #17', which is the next survey question are all to a certain degree connected. 'Question #11' shows that *Spotify* is the main source of music consumption to 82% and 89,4% [English and Norwegian version of the survey] of the survey respondents, while 'Question #15' shows that *Spotify* has high importance for the survey respondents when it comes to discovering new artists/music/podcasts.

The English version of the survey has 132 [26,5%] respondents who answered ‘4’, 130 [26,1%] which answered ‘3’, 121 [24,2%] which answered ‘2’, 72 [14,4%] which answered ‘5’, and 44 [8,8%] which answered 1. The Norwegian version of the survey has 154 [33,5%] respondents who answered ‘3’, 129 [28%] answered ‘4’, 76 [16,5%] answered ‘2’, 53 [11,5%] answered ‘5’, and 48 [10,4%] answered ‘1’. The biggest differences between the English and the Norwegian answers to this survey question, is that the English version has the most respondents on answer ‘4’ and have almost the same amount of response on answer ‘2’ and ‘4’, with 24,2% and 26,5% respectively, while the Norwegian version of this survey answer has a tighter top split between the answers ‘3’ and ‘4’, with 33,5% and 28%.

One thing is to ask the survey participants how much they are affected by the algorithmic recommendation engine of *Spotify*, and the actual effect of these algorithmic recommendations on the survey participants is a different thing. However, one could argue that the response to this survey question, both the Norwegian and the English versions of the survey, show that the survey participants at least are aware of the potential impact of the algorithmic recommendations on their discovery potential on the platform.

Question #17



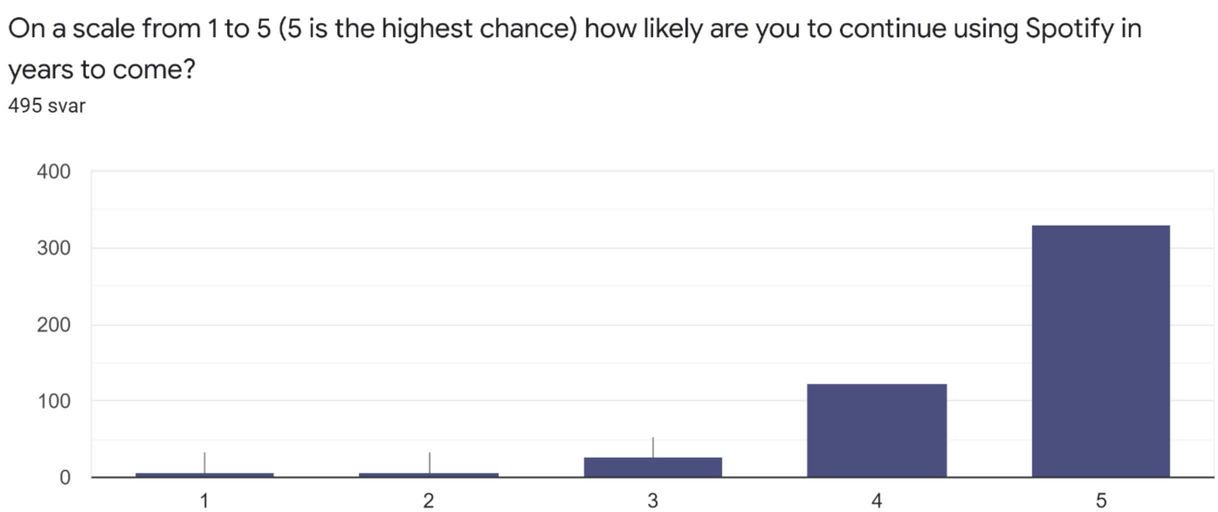
(Figure 5.14 "Question 17", above).

The seventeenth question of this survey is 'On a scale from 1 to 5 (5 is the highest value) are you worried about the possibility of the Spotify recommendation algorithm having a negative impact on your ability to discover new artists/genres/podcasts?'. This answers to this survey question, on both the English and the Norwegian version of the survey are perhaps the most alarming responses of the entire survey. The survey respondents answer that they are not worried about the recommendation algorithm having a negative impact, with the respondents on the English version of the survey answer 201 [40,5%] the '1' answer, 148 [29,8%] the '2' answer, 87 [17,5%] the '3' answer, 46 [9,3%] the '4' answer, and finally 14 [2,8%] the '5' answer. The Norwegian version of the survey has similar answers to this survey question, with 214 [46,6%] of the respondents answering the '1' answer, 112 [24,4] the '2' answer, 74 [16,1%] the '3' answer, 41 [8,9%] the '4' answer, and finally 18 [3,9%] answered the '5' answer alternative.

The answers to this survey question show that the survey respondents are not concerned about the potential negative impacts of *Spotify*'s recommendation algorithms. This could be quite problematic in the context of filter bubbles within the platform, especially when users discover being in a filter bubble. Suppose *Spotify* users are not worried about being in a filter bubble. In that case, it could arguably be difficult for them to understand that they are being affected by filter bubbles. Filter bubbles are the direct consequence of algorithmic recommendations being too good at their job to provide a personalized user experience based on user data and similar users. Counter-acting the filter bubble possibilities on an industry-leading platform such as *Spotify* will also help prevent the potential cultural power of such a platform since filter bubbles can be interpreted as algorithmically curated cultural censorship if it is allowed to go too far.

From the responses to this survey question, it seems like the survey respondents have a lot of confidence in the *Spotify* recommendation to be a positive influence on their discoveries within the platform. Perhaps *Spotify* has earned this trust from its users, by making good recommendations?

Question #18



(Figure 5.15 "Question 18", above).

The eighteenth question of this survey is ‘On a scale from 1 to 5 (5 is the highest chance) how likely are you to continue using Spotify in years to come?’. An overwhelming majority of the survey respondents of both the English and Norwegian version of the survey answered the answer alternative ‘5’ on this survey question, with 330 [66,7%] respondents on the English version, and 362 [78,4%] respondents on the Norwegian version of the survey.

The second largest answer alternative on both versions of the survey is ‘4’, with 124 [25,1%] respondents on the English version of the survey, and 72 [15,6%] respondents on the Norwegian version of the survey. The answer alternatives ‘1’, ‘2’, and ‘3’ got very low response rate on both version of the survey, with 7 [1,4%], 7 [1,4%] and 27 [5,5%] respondents on the English version of the survey, and 7 [1,5%], 3 [0,6%] and 18 [3,9%] respondents on the Norwegian version of the survey.

One of the reasons behind the answers to this survey question, can perhaps be attributed to *The Lindy Effect*, which can be described as:

“The longer something (non-perishable) exists, the longer it will exist. This can be applied to technology (smartphone vs telephone), ideas (communism vs capitalism), companies (Ford vs TikTok). So, in Essence, the objects we talk about can (in theory) live forever. [..] If you have two non-perishable things, the older one will survive, according to Lindy. This term came into popular use by the author *Nassim Nicholas Taleb* (*and Paul Skallas*)”. (Vervisch 2020).

One could argue that *Spotify*, the industry leading online music streaming service since the late 2000s/early 2010s are currently benefiting from *The Lindy Effect*. By consistently being the biggest platform for over a decade, it can be understandable that users are committed to the platform even though there are perhaps alternatives out there which would be a better fit for certain users, such as *Tidal* for users who are very concerned about sound-quality, or *Apple Music* for users who are heavily integrated into the *Apple* ecosystem. However, since *Spotify* is and has been the leading platform for such a long time as it has, it has become ‘the place to be’ for most users.

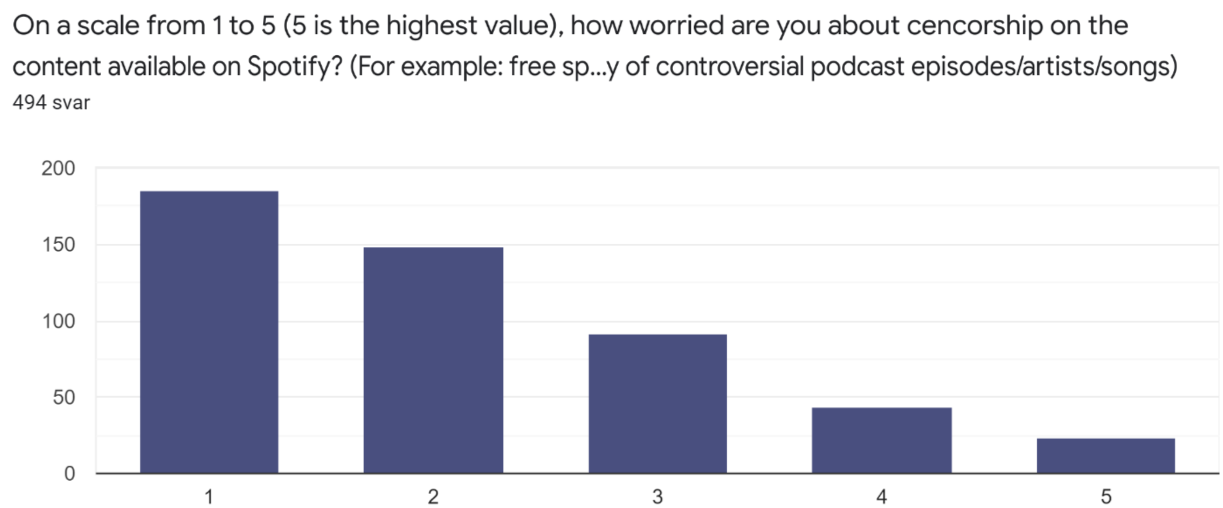
They have all their playlists which they perhaps have built up for years and years, they have their recommendations which keep getting better the longer the users stay on the platform, and perhaps most importantly, they have the path of least resistance. It is easy for the users to stay.

Question #19

(Figure 5.16 “Question 19”, above).

The nineteenth question of this survey is ‘On a scale from 1 to 5 (5 is the highest value), how worried are you about privacy of your data on Spotify?’. This survey question is perhaps not so directly relevant to the research questions of this thesis; however, it was still included to see if there was any noticeable difference between the respondents of the English and Norwegian version of the survey. There is not any noticeable difference found, and the largest answer-groups in both versions of the survey is ‘1’,’2’,’3’,’4’ and ‘5’, in chronological order. The answers to this survey question, combined with the fact that there is little concern about filter bubble effects among the survey respondents, could be somewhat alarming. Perhaps the average user of an online music streaming platform such as *Spotify* does not think about negative consequences of the technology behind the platforms in which they are using, at all?

Question #20

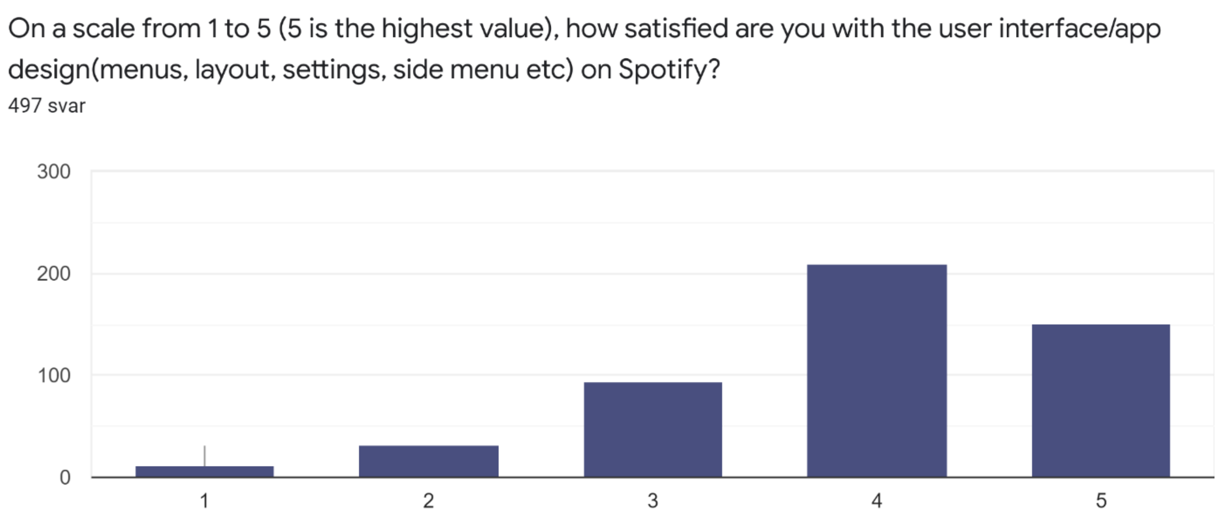


(Figure 5.17 “Question 20”, above).

The twentieth question of this survey is ‘On a scale from 1 to 5 (5 is the highest value), how worried are you about censorship on the content available on Spotify? (For example: free speech on podcasts, and availability of controversial podcast episodes/artists/songs)’. As with ‘Question 19’, this question is also not directly relevant to the research questions of this thesis, but the main intention is to see if there is any significant difference between the English and Norwegian survey respondents, when it comes to the subject of censorship on the *Spotify* platform. There is not any noticeable difference found between the Norwegian and English survey answers to this survey question, and the largest answer-groups in both versions of the survey is ‘1’,’2’,’3’,’4’, and ‘5’, in chronological order.

It is also essential to state that the data-gathering for this survey happened before the controversies involving one of the most popular podcasts in the world, the now *Spotify* exclusive *Joe Rogan Experience*, which includes removal of certain older episodes of the podcast from the catalogue, where the guests were controversial people, as well as more recent controversies surrounding the *Joe Rogan Experience* podcast which has involved podcast-guests with perhaps not so popular opinions on the pandemic management process in the US, as well as platform boycotting of *Spotify* by aging rock stars such as Neil Young and Joni Mitchell, because of said controversial podcast-guest. Perhaps the answers to this survey question would be somewhat different if they were recorded after these incidents, however, the importance of censorship on the *Spotify* platform is mere periphery when it comes to answering any research questions of this thesis, and therefore a rework within a new timeframe, for this survey question was not deemed necessary.

Question #21



(Figure 5.18 “Question 21”, above).

The twenty-first question of this survey is ‘On a scale from 1 to 5 (5 is the highest value), how satisfied are you with the user interface/app design (menus, layout, settings, side menu etc.) on Spotify?’.

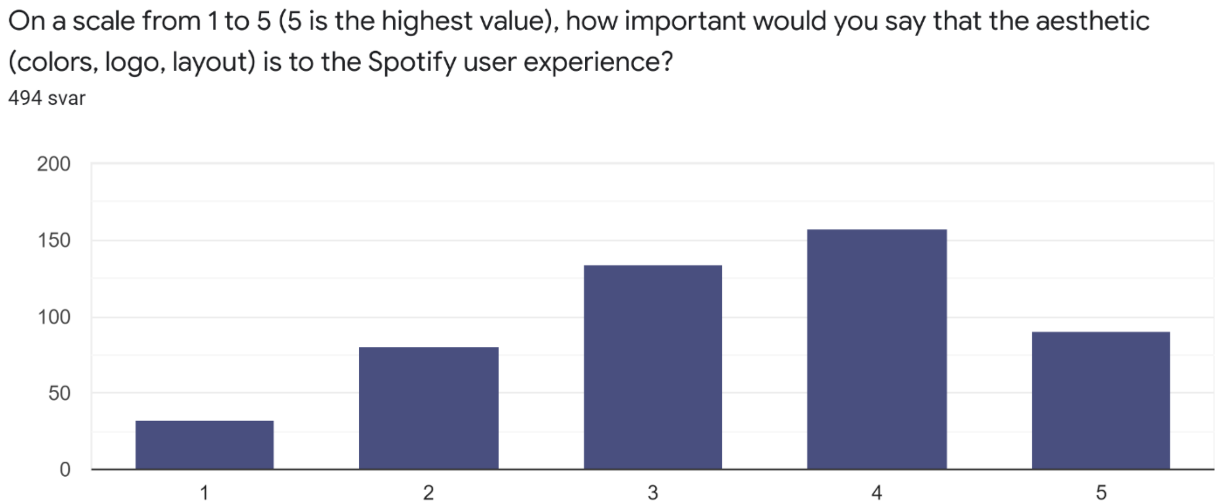
I would argue that the results gathered in the answers to this survey question, both in the English and Norwegian versions of the survey are a direct result of the *Spotify* platform utilizing key design theories such as those mentioned in the design analysis chapter, in combination with *The Lindy Effect*, which was mentioned earlier in this chapter when discussing ‘Question 18’.

The users are satisfied with the user interface/app design of the platform, since it adheres to *Gestalt Theory* and *Jakob's Law of Internet User Experience*, and because of how *The Lindy Effect* can work as an amplifier for *Jakob's Law of Internet User Experience*, in the case of *Spotify*.

Since *Spotify* has been the largest online music streaming platform since the late 2000s/early 2010s, one could assume that its competitors, like for example *Tidal* and *Apple Music*, are looking at the biggest platform in the industry through the lens of *Jakob's Law of Internet User Experience*, and therefore borrowing heavily from key design features to increase their relevancy and bring the path for least resistance closer for potential users that could be persuaded to change platforms. *The Lindy Effect* adds extra weight to this argument due to its connection to *Jakob's Law of Internet User Experience* in the context of *Spotify*. The leading platform has been number one for more than a decade, which brings its competitors to borrow design and functionality features, giving power to the leading platform as innovators and industry leaders.

The answers to this survey question in the English and Norwegian versions of this survey are quite similar, with 209 [42,1%] respondents answering the ‘4’ alternative on the English version, to 216 [47,1%] respondents on the Norwegian version. Then follows answer alternative ‘5’, with 151 [30,4%] and 145 [31,6%], ‘3’ with 94 [18,9%] and 75 [16,3%] respondents, ‘2’ with 32 [6,4%] and 19 [4,1%] respondents, and finally ‘1’ with 11 [2,2%] and 4 [0,9%] respondents, on the English and Norwegian versions of the survey.

Question #22



(Figure 5.19 “Question 22”, above).

The twenty-second question of this survey is ‘On a scale from 1 to 5 (5 is the highest value), how important would you say that the aesthetic (colors, logo, layout) is to the Spotify user experience?’. One of the main purposes behind this survey question, was to see if there was any significant difference between the Norwegian and English/international survey respondents. Another purpose was to see how much value the survey respondents put on aesthetics in the context of an online music streaming service platform.

The English version of the survey has 157 [31,8%] respondents answering alternative ‘4’, 134 [27,1%] answering ‘3’, 91 [18,4%] answering ‘5’, 80 [16,2%] answering ‘2’, and 32 [6,5%] answering the ‘1’ answer alternative. The Norwegian version of the survey has 145 [31,6%] respondents answering alternative ‘3’, 126 [27,5%] answering ‘4’, 79 [17,2%] answering ‘2’, 61 [13,3%] answering ‘5’, and 48 [10,5%] answering the ‘1’ answer alternative.

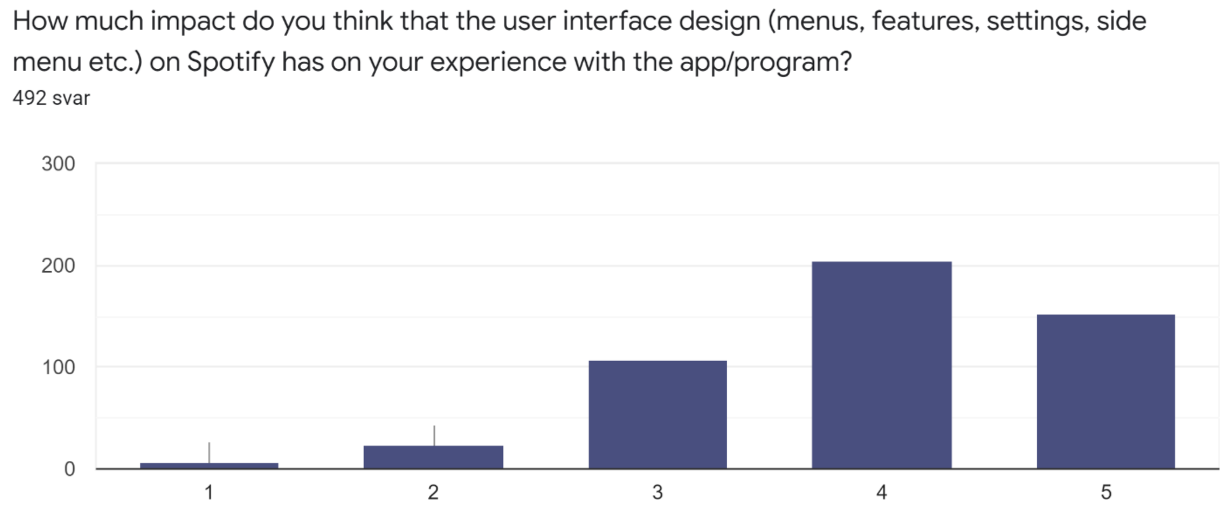
These results from the answers to this survey question shows that the English/international respondents are slightly more concerned with the aesthetic values of *Spotify*, than the Norwegian Survey respondents, with the English/international version of the survey having the most answers on the ‘4’ alternative, while the Norwegian version of the survey has the most answers to the ‘3’ alternative. Other than that, the answer results to this survey question does not reveal any significant difference between the Norwegian and English/international answers.

However, one could argue that the high importance placed on the aesthetic values of *Spotify* from the users of the platform, are somewhat unexpected. One could think that the users would be more concerned about the functional aspects of the platform, rather than aesthetic values such as colors, logo, and layout, but perhaps the technological development have come to a point in which functionality and technical aspects are taken for granted. Thorlacius (2007) explains this phenomenon more than a decade ago as:

“We have reached an era where the technical and functional aspects of a Web site [or application] are taken for granted. People just expect it to work. **The technology is viewed as a basic foundation for aesthetic experiences**.” (Thorlacius 2007).

One answer to why the survey respondents puts importance on the aesthetic aspects of the *Spotify* platform, could be that the survey sample group is somewhat biased towards younger people, with the ages 19 – 30 representing over 75% of the survey respondents. Younger people are perhaps more used to technology just working, and therefore puts more emphasis on the aesthetic aspects of the user experience on the *Spotify* platform.

Question #23



(Figure 5.20 “Question 23”, above).

The twenty-third question of this survey is ‘How much impact do you think that the user interface design (menus, features, settings, side menu etc.) on Spotify has on your experience with the app/program?’. Much like on the text about ‘Question 21’ in this survey, I would argue that the results of this survey question is connected to both key design theories which have been discussed earlier in this chapter, and in the design analysis chapter, as well as longevity theories such as *The Lindy Effect*, and the *Spotify* platforms status as the biggest online music streaming service for close to a decade. I combination of all these different factors, combined with an active UX and UI design team at *Spotify* which are working every day to make the platform easier to use, and more accessible for their users.

However, one question that one may ask after seeing the survey respondents results on a question such as this one, and ‘Question 21’ is if *Spotify* has good user interface/app design because of its position as the biggest platform in the space, or if the question can be flipped on its head. Is *Spotify* the biggest platform in the space because of its good user interface/app design? The answer to both questions can be challenging to answer, but one can assume that there is a connection between these two questions and that perhaps the answer can be more nuanced than a simple ‘Yes/No’ to either of the questions. A company does not become an industry leader such as *Spotify* without maximizing every aspect of its platform. Undoubtedly, UI/UX design has had a significant impact on the users' experience on the *Spotify* platform.

The answers to this survey question in the English and Norwegian versions of this survey are somewhat similar, with 204 [41,5%] respondents answering alternative ‘4’ on the English version, to 181 [39,4%] respondents on the Norwegian version. Then follows answer alternative ‘5’ with 152 [30,9%] and 114 [24,8%], ‘3’ with 107 [21,7%] and 127 [27,7%], ‘2’ with 23 [4,7%] and 31 [6,8%], and finally ‘1’ with 6 [1,2%] and 6 [1,3%] respondents, on the English and Norwegian versions of the survey. The biggest difference between the English and Norwegian versions of the survey, is that the second largest answer group are different, with the answer alternative ‘5’ being the second largest in the English version, while the Norwegian version has the alternative ‘3’ as the second largest answer alternative. Other than that, the answer distribution between the answer alternatives is similar between the two versions of the survey.

Question #24

The twenty-fourth and final question of this survey is ‘If you could add/change one feature to Spotify. What would it be?’. The idea behind this final question of the survey was to let the survey respondents have the opportunity to express any opinion or idea they have about the *Spotify* platform, which was not captured in the twenty-three survey questions before this one. In the process of allowing the survey respondents to express themselves as freely as possible, I concluded that allowing short sentence answers, such as on ‘Question 8’ and ‘Question 10’, was the best way to achieve this. Even though I would argue, as I have earlier in the thesis when discussing ‘Question 8’ and ‘Question 10’, that allowing short sentence answers in a quantitative survey such as this one, comes with its downsides.

It makes data visualization difficult, and the time spent versus reward from longer and unique answers is perhaps not worth it. However, having short sentence answers also brings up some interesting facts.

The three short-sentence answer questions in this survey, ‘Question 8’, ‘Question 10’, and ‘Question 24’, have received far fewer answers than the other survey questions. ‘Question 8’ has got 471 out of 503 respondents on the English version, and 422 out of 467 on the Norwegian version of the survey. ‘Question 10’ has got 431 out of 503 respondents on the English version, and 363 out of 467 on the Norwegian version of the survey. And finally, ‘Question 24’ has got 305 out of 503 respondents on the English version, and 229 out of 467 respondents on the Norwegian version of the survey. To put these numbers into perspective, every other survey question besides the three short sentence answer questions on the English version got at least 492 responses out of the 503 total survey respondents of the survey. The Norwegian version is similar, with the minimum responses on every other survey question besides the three short sentence answer questions being 459 out of 467 total survey respondents.

One of the reasons why the short sentence answer questions in this survey have received far fewer answers than the other types of survey questions could be because they require more effort from the survey respondents.

For the survey respondents to choose on a scale from one to five whether they agree with a statement or not. Choosing between three or four multiple-choice answers requires little effort and very little creativity from the survey respondents. Short sentence answers like ‘Question 23’, on the other hand, require the survey respondents to think outside of the limited answer choices which have been available in the other survey questions.

The answers to ‘Question 23’ on both the English and Norwegian versions of the survey are varied, however, there are some repeating tendencies. Answers along the lines of the following: ‘Playlist configuration’, ‘More variation in ads’, ‘Offline usability’, ‘Improved friend activity’, ‘Reduced Spotify Premium costs’, ‘Improved recommendations’, ‘Shuffle improvements’, ‘Better sound quality’, ‘Different color themes’, and ‘Pay the artists more’, are some of the most popular answers to this survey question.

However, the most common answer to this survey question is variations of: ‘Nothing’, ‘I don’t know’ and ‘None’. Perhaps *Spotify* is either incredibly well optimized, or the users have become habituated. These answers, combined with the non-answers to this survey question, form most responses to this survey question. One could draw parallels to the answers to ‘Question 23’, and the need for good recommendation engines. The survey respondents are paralyzed by action due to the seemingly infinite answer possibilities of ‘Question 23’.

5.1 Survey summary and findings

In this concluding section of the ‘Survey’ chapter, I will summarize the key findings from the English/International and Norwegian versions of the survey and address the main differences and similarities between the responses from the survey's English/International and Norwegian versions.

The English/International and Norwegians' answers to the survey questions have, for the most part, been quite similar to each other. With the one exception being the answers to ‘Question 7’, if the survey respondents are using *Spotify Premium* or *Spotify Free*, where almost every Norwegian respondent (95,5%) answered that they are subscribed to the *Spotify Premium* feature. In contrast, the English/International survey respondents' answers were somewhat lower in the *Spotify Premium* department (77,4%). One logical reason for this, as stated in the ‘Question 7’ section, could be the economic situation in Norway, compared to many other places in the world.

There are some slightly worrying yet not surprising findings throughout the survey responses. I would highlight the responses to survey questions 15, 16, 17, 19, and 20 as the most significant concerns. The responses to these survey questions show that the survey respondents are mainly relying on *Spotify* to discover new artists/music/podcasts. Their reliance on the *Spotify* recommendation algorithms for these discoveries is relatively high. The survey respondents are not worried about the possibility of the *Spotify* recommendation algorithms harming their abilities to discover new content on the platform. They do not worry about their data, privacy, or censorship on the *Spotify* platform.

Perhaps these findings say more about the average streaming service user than it does about the most significant online music streaming platforms or any online streaming service. Are we too willing to disregard the potential negative consequences of the online streaming platforms if we are satisfied with the content we receive from these platforms?

6. Summary and conclusion

This final chapter aims to conclude this thesis by summarizing key research findings concerning the research goals and research questions and the value and contribution thereof. I will also review the limitations of this thesis and propose opportunities for future research.

6.1 Conclusion

So, **'How is *Spotify* as a music streaming platform changing how we consume and discover music?'.**

This is the main research question of this thesis, and what I have been trying to come close to an answer to, through the three sub-questions: "**How do online recommendation engines shape human behavior?"**, **"Are users aware of to which extent their decisions are affected by recommendation engines and user experience design?"** and "**How does user experience design on a platform such as *Spotify* amplify change in human behavior and decision making?".**

When it comes to the first of the three sub-questions of this thesis, I have found that online recommendation engines shape human behavior by amplifying the already established tastes and preferences of the users, as well as recommending new content which are in the periphery of the tastes and preferences of the users, by deploying 'nearest neighborhood' algorithmic recommendations. The survey respondents also show that they are not very concerned about the potential 'filter bubble' problem and seem to be content with the algorithmic and design-based recommendations occurring within the online music streaming platforms presented in this thesis.

The second sub-question of this thesis from looking at the results from the quantitative surveys used in this thesis, it can seem like the *Spotify* users are not too aware of to which extent their decisions are affected by recommendation engines and user experience design.

The survey respondents answered that they to a large degree are not concerned about the possibility of the *Spotify* recommendation algorithm having a negative impact on their ability to discover new artists/genres/podcasts, and user experience design theories such as *Jakobs Law of Internet User Experience* and *Gestalt Theory* have such a presence in not only platforms such as *Spotify*, *Tidal* or *Apple Music*, but large parts of the internet, that good and smart user experience design is perhaps expected by the users of an industry-leading platform, such as *Spotify*. The users could be aware of how the decisions are affected by recommendation engines and user experience design. However, I would argue that this is something that perhaps the average users are not interested enough in. To reach the level of awareness to start counteracting this has been somewhat proven, with the fact that the users are not afraid of the 'filter bubble' problem. However, this sub-question is challenging to conclude an answer to and could perhaps be improved upon by further research.

The third sub-question, which is **"How does user experience design on a platform such as *Spotify* amplify change in human behavior and decision making?"** Can be challenging to provide an exact answer. However, through design-based recommendations, as well as key user interface and user experience design theories such as *Path of least resistance* as well as *Gestalt Theory*, *Jakobs Law of Internet User Experience*, it is clear that the users of the *Spotify* platform is being presented with choices which are likely to keep the users engaged in the platform, as well as a good mix between discovering new content, and going back to frequently used content such as self-made playlists, and favorite artists. The symbiosis between algorithmic and design-based recommendations and good and proven user experience design gets the users hooked and retained on the platform.

To provide an answer to the main research question of this thesis has been a challenging and humbling experience. I will not claim to have a concise answer to **"How is *Spotify* as a music streaming platform changing how we consume and discover music?"**

However, I would argue that my work on this thesis can help highlight how the combination of **algorithmic** recommendations, **design-based** recommendations, and **user experience design** are all connected, when it comes to providing the users of online music streaming platforms with the content they are craving, as well as the content they did not know they wanted until they were recommended it.

6.2 Limitations

This research work has provided some valuable findings on *Spotify* users listening habits from the results of the quantitative surveys. The fact that I was able to gather almost 1000 responses from the English/International and Norwegian versions of the survey combined is something I am satisfied with. However, as mentioned in the methodology chapter of this thesis, the potential bias in the survey sample is a potential limitation towards the results and relevancy of the survey answers.

The surveys created and used for this thesis have some areas that could be improved upon when it comes to statistical analysis of the survey data. The fact that the English/International and Norwegian versions of the survey include different types of answer methods, ranging from 'Yes/No' type answers, to 'Multiple choice' type answers, to 'On a scale from 1 to 5 (5 is the highest value)' type gradient answer, to 'Short sentence' type answers, have made it difficult to do a more traditional type of statistical analysis of the surveys.

In hindsight, some more questions could have been added to the surveys, which again could have improved upon the surveys. The English/International version of the survey should have a question or two in relation to geolocation, as this would have provided a more specific overview of from where the results are coming from, instead of just 'English/International' part of the world. Another potential limitation of the surveys is that they do not include any questions about how the covid-19 pandemic have affected their listening patterns.

This could provide relevancy since the survey answers were being gathered while the pandemic and lockdowns were a strong presence in peoples everyday lives. However, the fact that the survey was collecting data between September 24th, 2020, and May 2nd, 2021, can perhaps be a positive thing for future research, due to its insight into the users habits on the *Spotify* platform during the covid-19 pandemic.

6.3 Future research

This study primarily serves as an initial discussion about the effects of both recommendation engines and user experience design on the users of an online music streaming platform such as *Spotify*. Many similar studies have focused on either the recommendation engine aspect, or the user experience design aspect of online platforms. However, I have yet to find any which are specifically focused on how recommendation engines and user experience design work together to guide users towards certain content of the platform. This thesis, provides some insights into that important relationship and future research may benefit from analysis of the relationship of recommendation engines and user experience design.

This study can also provide a valuable insight into the listening habits of *Spotify* users during the Covid-19 pandemic. Perhaps, if future research is to be done on the effects of the Covid-19 pandemic on listening habits of *Spotify* users, the data from the surveys created for this thesis could help provide some insight into this.

In the future, it is important that scholars and researchers that are looking into platforms which can have a large impact on the cultural development of, in the case of this study, music, to remain critical, and curious, to the motives and functionalities of these platforms. Because if we will not be critical and curious, then who will be? And what will the consequences be?

Perhaps a culture determined by algorithms? Only time will tell.

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7.1 Appendix 1, English/International survey

Survey about Spotify

Survey about listening habits, and the effects of online recommendation engines and application design on user choices. For use in a masters thesis in digital culture, at the university of Bergen, fall 2020 - spring 2021. This survey is anonymous

*Må fylles ut

1. Are you, or have you been a Spotify user? (If the answer is no, then there is no need to answer the rest of the survey) *

   Markér bare én oval.

   - Yes
   - No

2. Are you male or female?

   Markér bare én oval.

   - Female
   - Male
   - Other

3. How old are you?

   Markér bare én oval.

   - Under 18
   - 18
   - 19 - 24
   - 25 - 30
   - 31 - 36
   - 37 - 42
   - Over 42

4. Do you listen mostly to music or podcasts on Spotify?

Markér bare én oval.

- Music
- Podcasts
- Other (comedy, meditation, ambient sounds etc.)

5. On which device do you use Spotify the most?

Markér bare én oval.

- Phone
- Laptop/Desktop computer
- Tablet
- Other

6. Where do you mostly use Spotify?

Markér bare én oval.

- Commuting to and from work/school
- In the car
- While studying and/or working
- While at the gym, and/or doing other physical activities
- While at home and/or relaxing
- While playing video games
- Other

7. Which version of Spotify do you use?

Markér bare én oval.

- Spotify Premium
- Spotify Free

8. Why do you use the premium or free version of Spotify?

____

9. Have you used other music/podcast streaming services than Spotify?

Markér bare én oval.

- Yes
- No
- I don't know

10. Why do you use Spotify over other music/podcast streaming services?

____

11. is Spotify your main source of music consumption?

Markér bare én oval.

- Yes
- No
- Maybe/I don't know

12. Which of the alternatives/features below do you listen to the most, when using Spotify?

Markér bare én oval.

- Your own playlists
- Full albums
- Genre & Moods
- Discover (for example "Discover Weekly and "Release Radar" playlists generated for you)
- Charts (for example "Top 50 by Country", "Top 50 Global", or "Viral 50 Global")
- Other peoples playlists

13. How much time do you spend on average, listening to music/podcasts on Spotify per day?

Markér bare én oval.

- under 1 hour
- 1 - 2 hours
- 2 - 4 hours
- 4 - 6 hours
- 6 - 8 hours
- 8+ hours

14. On a scale of 1 to (5 has the highest value) how easy do you think Spotify is to use?

Markér bare én oval.

	1	2	3	4	5	
Difficult to use						Very easy to use

15. On a scale from 1 to 5 (5 is the highest value) how important is Spotify for you, when it comes to discovering new artists/music/podcasts?

Markér bare én oval.

	1	2	3	4	5	
Not important	◯	◯	◯	◯	◯	Very important

16. On a scale from 1 to 5 (5 is the highest value) how much impact does the Spotify recommendation algorithm (playlists based on your listening habits, and artist/songs/podcasts based on your listening habits) have on how you discover new artists/music/podcasts?

Markér bare én oval.

	1	2	3	4	5	
No impact	◯	◯	◯	◯	◯	Very impactful

17. On a scale from 1 to 5 (5 is the highest value) are you worried about the possibility of the Spotify recommendation algorithm having a negative impact on your ability to discover new artists/genres/podcasts?

Markér bare én oval.

	1	2	3	4	5	
Not worried	◯	◯	◯	◯	◯	Very worried

18. On a scale from 1 to 5 (5 is the highest chance) how likely are you to continue using Spotify in years to come?

Markér bare én oval.

	1	2	3	4	5	
Will switch to another platform	◯	◯	◯	◯	◯	High chance to stay

19. On a scale from 1 to 5 (5 is the highest value), how worried are you about privacy of your data on Spotify?

Markér bare én oval.

	1	2	3	4	5	
Not worried	◯	◯	◯	◯	◯	Very concerned

20. On a scale from 1 to 5 (5 is the highest value), how worried are you about cencorship on the content available on Spotify? (For example: free speech on podcasts, and availability of controversial podcast episodes/artists/songs)

Markér bare én oval.

	1	2	3	4	5	
Not worried	◯	◯	◯	◯	◯	Very concerned

21. On a scale from 1 to 5 (5 is the highest value), how satisfied are you with the user interface/app design(menus, layout, settings, side menu etc) on Spotify?

Markér bare én oval.

	1	2	3	4	5	
Unhappy	◯	◯	◯	◯	◯	Very pleased

22. On a scale from 1 to 5 (5 is the highest value), how important would you say that the aesthetic (colors, logo, layout) is to the Spotify user experience?

Markér bare én oval.

	1	2	3	4	5	
Not important	◯	◯	◯	◯	◯	Very important

23. How much impact do you think that the user interface design (menus, features, settings, side menu etc.) on Spotify has on your experience with the app/program?

Markér bare én oval.

	1	2	3	4	5	
No impact	◯	◯	◯	◯	◯	Very important for the user experience

24. If you could add/change one feature to Spotify. What would it be?

Dette innholdet er ikke laget eller godkjent av Google.

Google Skjemaer

7.1.2 Complete dataset English/International version

Complete dataset from the 504 answers from the English/International version of the survey is available at:

https://docs.google.com/spreadsheets/d/1or_bGeKY58nbomwbuP7T0sUr1YBG0noCGJQ14l07Keg/edit?usp=sharing

7.2 Appendix 2, Norwegian survey

Spørreundersøkelse om Spotify

Spørreundersøkelse om lyttevaner, og effekten av applikasjonsdesign på brukervalg. For bruk i masteroppgave i digital kultur, ved universitetet i bergen høsten 2020 - våren 2021. Denne spørreundersøkelsen er anonym.

*Må fylles ut

1. Bruker du, eller har du brukt Spotify? Om svaret er nei trenger du ikke svare på resten av spørsmålene. *

Markér bare én oval.

- Ja
- Nei

2. Er du mann eller kvinne?

Markér bare én oval.

- Mann
- Kvinne
- Annet

3. Hvor gammel er du?

Markér bare én oval.

- Under 18
- 18
- 19 - 24
- 25 - 30
- 31 - 36
- 37 - 42
- Over 42

https://docs.google.com/forms/d/1jtJXvjn-F_R7Ht3r7CqVnlsBghSUfiDO5NFJLylTJt0/edit 1/8

4. Bruker du Spotify til å lytte til musikk, eller til å lytte til podkaster?

Markér bare én oval.

- Musikk
- Podkaster
- Annet (Stand-up komedie, meditasjonslyder, ASMR osv.)

5. Hva slags enhet bruker du oftest når du lytter til Spotify?

Markér bare én oval.

- Telefon
- Laptop/PC
- Tablet
- Annet

6. Hvor bruker du Spotify mest?

Markér bare én oval.

- Når jeg pendler til og fra jobb/skole
- Når jeg kjører bil
- Når jeg studerer og/eller jobber
- Når jeg er på treningssenter, og/eller gjør andre fysiske aktiviteter
- Når jeg er hjemme og/eller slapper av
- Når jeg spiller dataspill
- Annet

7. Hvilken versjon av Spotify bruker du?

Markér bare én oval.

- Spotify Premium
- Spotify Free

8. Hvorfor bruker du Premium-versjonen, eller Free-versjonen av Spotify?

9. Har du brukt andre musikk/podkast streaming programmer/apper enn Spotify?

Markér bare én oval.

- Ja
- Nei
- Jeg vet ikke

10. Hvorfor foretrekker du Spotify over andre musikk/podkast streaming programmer/apper?

11. Er Spotify din største kilde til musikk i hverdagen?

Markér bare én oval.

- Ja
- Nei
- Jeg vet ikke

12. Hvilket av alternativene nedenfor lytter du mest til når du bruker Spotify?

Markér bare én oval.

- Mine egne spillelister
- Hele album
- Genre og/eller Moods
- Discover (for eksempel "Discover Weekly" og "Release Radar" spillelister generert for deg)
- Topplister (for eksempel "Top 50 i Norge", "Top 50 Global", eller "Viral 50 Global")
- Spillelister laget av andre (for eksempel venner, bekjente, kjendiser osv.)

13. Hvor mye tid bruker du på å lytte til Spotify i løpet av en dag?

Markér bare én oval.

- under 1 time
- 1 - 2 timer
- 2 - 4 timer
- 4 - 6 timer
- 6 - 8 timer
- 8+ timer

14. På en skala fra 1 til (5 har høyest verdi) hvor enkelt synes du Spotify er å bruke?

Markér bare én oval.

	1	2	3	4	5	
Vanskelig						Veldig enkelt

15. På en skala fra 1 til 5 (5 har høyest verdi) hvor viktig er Spotify for deg når det kommer til å oppdage nye artister, ny musikk, eller nye podkaster?

Markér bare én oval.

	1	2	3	4	5	
Ikke viktig	◯	◯	◯	◯	◯	Veldig viktig

16. Spotify benytter seg av en anbefalingsalgoritme, som baserer seg på dine lyttevaner, og danner foreslåtte spillelister ut ifra dette. På en skala fra 1 til 5 (5 har høyest verdi) hvor stor påvirkning tror du disse listene fra Spotify har på hvordan du oppdager nye artister, ny musikk, eller nye podkaster?

Markér bare én oval.

	1	2	3	4	5	
Liten påvirking	◯	◯	◯	◯	◯	Enorm påvirking

17. På en skala fra 1 til 5 (5 er den høyeste verdien) er du bekymret for muligheten for at Spotify-anbefalingsalgoritmen har en negativ innvirkning på din evne til å oppdage nye artister / sjangere / podkaster?

Markér bare én oval.

	1	2	3	4	5	
Ikke bekymret	◯	◯	◯	◯	◯	Veldig bekymret

18. På en skala fra 1 til 5 (5 er den høyeste sjansen) hvor sannsynlig er det at du fortsetter å bruke Spotify i årene som kommer?

Markér bare én oval.

	1	2	3	4	5	
Jeg kommer til å bytte til noe annet	◯	◯	◯	◯	◯	Fortsetter med Spotify

19. På en skala fra 1 til 5 (5 er den høyeste verdien), hvor bekymret er du for personvernet til dataene dine på Spotify?

Markér bare én oval.

	1	2	3	4	5	
Ikke bekymret	◯	◯	◯	◯	◯	Veldig bekymret

20. På en skala fra 1 til 5 (5 er den høyeste verdien), hvor bekymret er du for sensur på innholdet som er tilgjengelig på Spotify? (For eksempel: ytringsfrihet på podkaster, og tilgjengeligheten av kontroversielle podkast-episoder / artister / sanger)

Markér bare én oval.

	1	2	3	4	5	
Ikke bekymret	◯	◯	◯	◯	◯	Veldig bekymret

21. På en skala fra 1 til 5 (5 er den høyeste verdien), hvor fornøyd er du med brukergrensesnittet / appdesignet (menyer, layout, innstillinger, sidemeny osv.) På Spotify?

Markér bare én oval.

	1	2	3	4	5	
Ikke fornøyd	◯	◯	◯	◯	◯	Veldig fornøyd

22. På en skala fra 1 til 5 (5 er den høyeste verdien), hvor viktig vil du si at det estetiske (farger, logo, layout) er for Spotify-brukeropplevelsen din?

Markér bare én oval.

	1	2	3	4	5	
Ikke viktig	◯	◯	◯	◯	◯	Veldig viktig

23. Hvor stor innvirkning tror du at brukergrensesnittdesignet (menyer, funksjoner, innstillinger, sidemeny osv.) har på din opplevelse av tjenesten Spotify?

Markér bare én oval.

	1	2	3	4	5	
Ingen innvirkning	◯	◯	◯	◯	◯	Veldig viktig

24. Hva ville du gjort om du kunne lagt til eller endret en funksjon i Spotify?

Dette innholdet er ikke laget eller godkjent av Google.

Google Skjemaer

7.2.2 Complete dataset Norwegian version

Complete dataset from the 468 answers from the Norwegian version of the survey is available at: https://docs.google.com/spreadsheets/d/1vlVU-VsO9Z1PYT97zfVMSfGjrKTuRFPSeLC1cTJ_M18/edit#gid=1395556706

7.3 Table of figures