User Loyalty and Willingness to Pay for a Music Streaming Subscription

Identifying Asset Specificity in the Case of Streaming Platforms

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Abstract

Music streaming has increased industry revenue and displaced piracy, but limited profits for artists. In this thesis, I examine user loyalty to streaming platforms, focusing on the asset specificity of features and estimating what users are willing to pay for each of these features. A structural equation model of survey data shows that feature satisfaction positively affects both asset specificity of and overall satisfaction with streaming platforms, strengthening user loyalty. Using conjoint analysis (hedonic feature analysis), I estimate that users are willing to pay at least $14.40 per month for platforms that offer algorithm, playlist and social features, and the ability to download music.

JEL classification: D49, M21, O33, Z11

Keywords: music streaming, asset specificity, willingness to pay, conjoint analysis, consumer loyalty, structural equation modeling

1. Introduction

In the past decade, streaming has changed the landscape of the music industry by providing a constant stream of revenue to the platforms and labels, at the cost of the artists. Music streaming platforms have grown exponentially since they were first introduced in the early 2000s, at a time when digital music piracy was at an all-time high and physical and digital sales were declining. By bundling unlimited tracks and offering them at a flat monthly subscription price, streaming platforms were able to convince people to pay for music consumption again and save the industry. However, even after a decade of demand growth and platform development, the streaming platforms are charging the same prices and barely starting to make money, while artists are struggling to survive off revenue from digital sales, as they used to with physical sales. [1] This paper investigates users' relationships with music streaming platforms to understand their loyalty and willingness to pay for their current platform subscription. The customization, uniqueness, and low degree of transferability in a platform's features qualify it as a specific asset and prove market power to justify an increase in a platform's subscription price, and thus increase the share of revenue that the artists receive. [2,3]

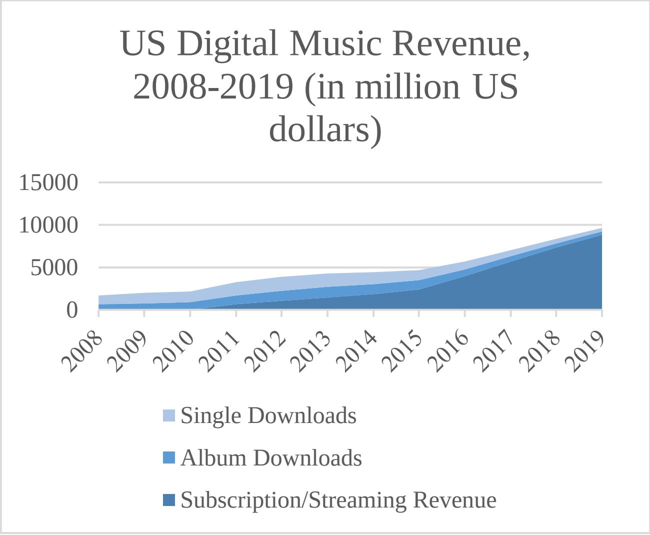
Before streaming and bundled music purchases, songs were bought "a la carte". Digitization of music first began in 1983 with compact discs, and the popular mp3 file was introduced in 1990. Instead of having to purchase an entire album, users could purchase individual song files. This ease to purchase and send files over the internet led to the creation of file-sharing platforms, the most popular one being Napster. People could pirate as much music as they wanted from programs like Napster for free instead of paying the $0.99 on iTunes, which was introduced with the iPod in 2001. According to the RIAA, this period of piracy saw a 47% decrease in revenue for the music industry at the time between 1999 and 2009. Music streaming services Spotify and Deezer first introduced the "freemium" business model to attract users with a subscription and turn them into paid users. [4] Once these platforms, and the ones that followed, grew their user base, the music industry started to see an increase in revenue. Aguiar & Waldfogel (2015) set out to investigate if streaming services would bring the lost revenue back

[1] See www.investopedia.com/articles/investing/120314/spotify-makes-internet-music-make-money.asp.
[2] Inability or difficulty to transfer data from one platform to another platform
[3] A specific asset is one that requires human, physical, or time investments to the point that switching from that asset relationship to another would entail significant switching costs, thus leaving the consumer dependent on that original relationship.
[4] Free ad-based listening subscription plan

to the music industry and most of the research found that they would create at least the same, if not more, revenue for the industry. The US recorded music industry grew 12% to $9.8 billion in 2019, which was driven by the streaming platforms. [5] It became clear that consumers were willing to pay for convenience when they subscribed to a streaming platform (Kreuger, 2019). Figure 1 shows that while streaming revenue was growing in the early 2000s, it was displacing and expanding digital album and singles' sales revenue.

1.1 The Growth of Streaming

Figure 1



Streaming started to become more popular in the early 2000s with non-interactive streaming platforms. Non-interactive platforms are different from radio because they curate music for the listener based on which artist or genre that listener chooses, collecting data from their listening patterns. These platforms are similar to radio in the sense that they collect revenue from advertisements placed in between songs. Pandora was launched in 2005 and became one of the most popular free online radio services, known for having a strong user algorithm to recommend new music. In 2009, Pandora started offering a higher tier subscription at $3.99 monthly, with no ads and higher quality listening for users. Sirius XM was developed in 2007, which offered a large catalog of radio programs as well as original content to its subscribers for $15 per month.

[5] RIAA

Following non-interactive platforms were interactive platforms, which allow users to pick and choose the song, album or artist that they want to listen to. This was very different from what was already available because it allowed users to rent a bundle of music instead of buying individual songs “a la carte”, like with iTunes. Once mobile devices became popular, streaming revenue began to grow rapidly (Kreuger, 2019). Non-interactive streaming platforms were mainly making their revenue from advertisement-based listening, while interactive streaming platforms earned revenue from paid monthly subscriptions.

Spotify launched in 2006 and was one of the first successful platforms to create a freemium streaming model for music, which gave listeners an option to listen for free with commercials, in the hopes of eventually getting them to pay for the $9.99 monthly subscription. [6] The founder of Spotify, Daniel Ek, explained that the goal was to create a platform that was better than piracy to obtain music.[7] For this reason, Spotify set low prices and offered new pricing tiers to students and families in order to compete with the free alternative. This paved the way for new interactive streaming platforms to price similarly. Apple, which dominated the digital market with iTunes in the early 2000s, developed its own on-demand streaming platform called Apple Music in 2015. They entered the streaming landscape well after Spotify and tried to appeal to new users with their curated playlists that would help listeners find relevant and new music (Forbes, 2015). Tidal, which now offers the highest paid subscription, was purchased by Jay Z in 2015 from Aspiro and relaunched as an “artist-backed alternative to Spotify or Pandora (Business Insider). Their competitive business plan is to be a platform that gives its users access to the exclusives of big-name musicians, such as Kanye West, Rhianna, and Beyoncé, while guaranteeing the best quality of audio. This attracts a user demographic of artists and die-hard music fans. However, Tidal has only found short term success from this business model and has also faced backlash from lying about subscriber and streaming numbers. Soundcloud, another platform, started more global than the other platforms and in 2014, with its free subscription, had the largest number of monthly music listeners second only to YouTube. It allows users to upload, promote, and share audio and recently introduced the premiere partner program that allows record labels to monetize their content on the platform. However, this introduced a subscription

[6] Rhapsody, another online on-demand streaming service, was introduced earlier in 2001 but failed to get a lot of users because of the higher price at the time when free music consumption was at its peak.
[7] See freakonomics.com/podcast/spotify

fee to Soundcloud users who want to listen to that content and save music offline. Emerging artists are using the platform to try to gain traction for their music, and established artists are using the platform to interact with the fans who are streaming their music (Nanda and Steen, 2019). YouTube Music was developed in 2015 and revamped in 2018, replacing Google Music Play, which was launched in 2013, trying to entice users into the Google community. YouTube Music aims to attract more casual listeners than the other streaming platforms and provides partner deals with YouTube shows through its subscription. Additionally, artists can post their music to YouTube videos, and those videos collect royalties on the song and prevent other users from posting or monetizing from another artist’s song. Deezer is a French online music streaming service that was developed in 2007, but not made available to the US until 2016. The platform currently has fourteen-million users in over 180 countries.

1.2 Streaming Platforms

The most popular streaming platforms in the United States are shown in Table 1, along with their model, pricing, and users to date. The interactive platforms offer the ability for users to follow each other, create and share playlists, and curate music towards the listeners tastes and listening patterns. According to Statista (2019), the music streaming segment had 872 million users in 2019 and predicts to have 978 million users by 2023. This paper looks at all interactive music streaming platforms, since most have adopted similar models. However, there will be a slight focus on Spotify because it was the model platform and relies solely on its streaming revenue, whereas other interactive platforms such as Apple Music and Google Play can sustain revenue loss because of the revenue generated by the parent companies. Also, since the company went public in 2017, more data is available for Spotify than for other streaming platforms.

Table 1: Popular U.S. Streaming Platforms

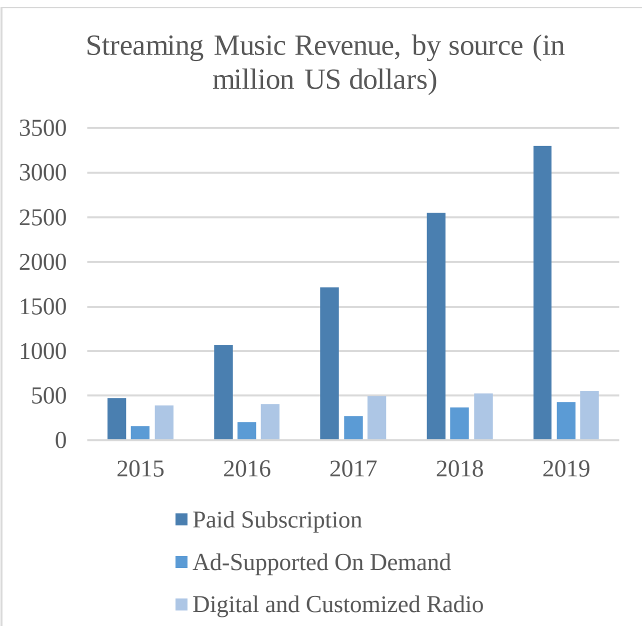
	SPOTIFY	**APPLE MUSIC**	**SOUNDCLOUD**	**PANDORA**	**SIRIUS XM**	**DEEZER**	**TIDAL**	**YOUTUBE/GOOGLE PLAY**
YEAR CREATED	2006	2015	2007	2005	2007	2007	2015	2015
FREEMIUM MODEL	X		X	X		X		
INTERACTIVE	X	X	X			X	X	
$4.99 (STUDENT) PLAN	X	X	X	X	X			X
$9.99 (PREMIUM) PLAN	X	X	X	X			X	X
$14.99 (FAMILY) PLAN	X	X	X		X			X
$19.99 PLAN							X	

ACTIVE US USERS (IN MILLIONS)	44.2	44.5	15.31	31.47	7.6	7	3	21.77

(Verto Analytics, 2019)

The subscription prices for these streaming platforms range from $4.99 to $19.99, with different membership discounts and deals for students and family, as a way to price discriminate for different user populations. Currently, Tidal is the only streaming platform that offers a subscription plan at a price higher than $14.99, since it was made to help artists earn more royalties from their streamed music. The largest age group of users is 25-34, followed by the 18-24 age group (Statista 2019). The fact that hip-hop, R&B, and EDM have the highest album sales on streaming services reflects that that user base is relatively young and urban (Kreuger, 2019). [8,9] Additionally, in 2018 30% of users were in the low-income bracket, while 50% of users were in the high-income bracket. [10]

Figure 2



RIAA, 2019

While music streaming platforms have increased the amount of revenue coming to the music industry, especially with the growth of paid subscribers as seen in Figure 2, there have been disputes over whether artists are getting paid fairly (Rolling Stone). Spotify pays back

8 Rhythm & Blues
9 Electronic Dance Music
10 See http://www.statista.com/outlook/202/109/digital-music/united-states#market-ageGroupGender

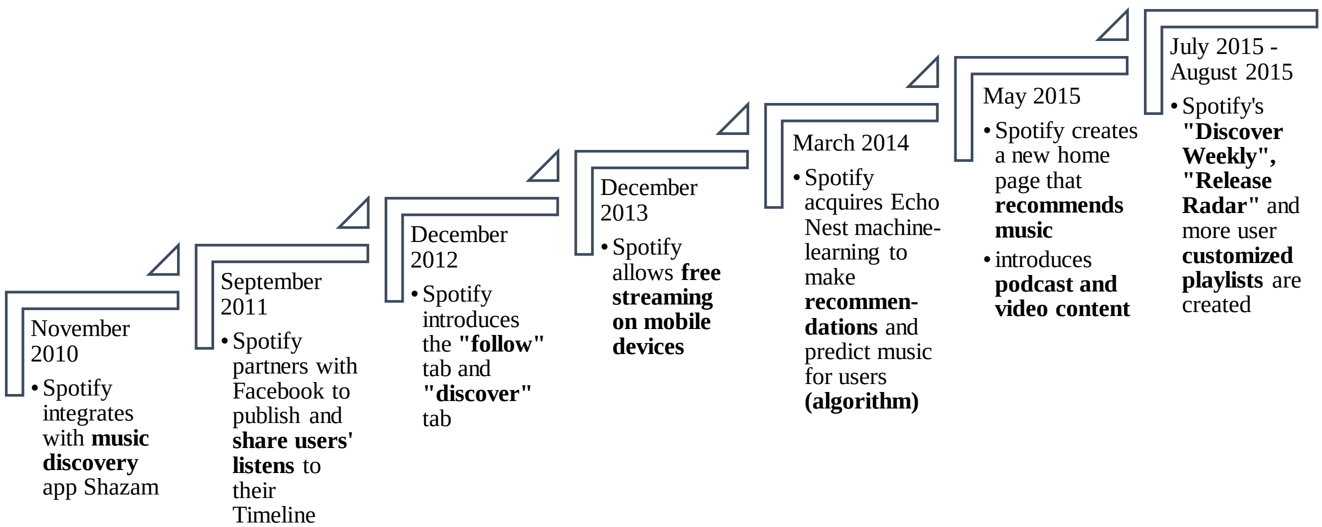
roughly 70% of streaming revenue in royalties based on the number of streams. If a user is paying $10 a month, about $6 goes to the owner of the recording, $1 goes to the owner of the copyright, and Spotify keeps $3. [11] The amount that the artist makes varies depending on the royalty agreements with the labels, but it usually ends up being around $0.004-$0.006 per stream. While a lot of revenue to the artists has to do with their agreements with the records labels, there has been backlash from artists like Taylor Swift to take her music off of Spotify in 2014 and Apple Music in 2015 for their failure to pay artists fairly. Aloe Blacc spoke out against Spotify's payments to the songwriters, while artists like Beyoncé and Jay-Z created Tidal to make royalty payments fairer for all artists on the platform by charging their users a higher subscription price. While it depends on location and royalty rate agreements with labels, on average Tidal pays artists $0.01284 per stream, Apple Music pays artists $0.00782 per stream, and Spotify pays artists $0.00437 per stream.[12]

While Spotify's user base has increased every year, especially with the family plan subscription, the revenue per listener has been falling (Bloomberg 2019). In 2017, Spotify lost $1.4 billion from $5 billion of revenue. Kreuger hypothesizes that in order for Spotify to become profitable, it will have to raise monthly subscription fees above the rates of its competitors without losing subscribers (Kreuger, 2019). Spotify founder Daniel Ek claims that Spotify cannot raise prices because people are not as willing to pay $10, let alone a higher amount. He argues that people would go back to pirating music on third party sites or through mp3 converters, as they did a few years ago before Spotify was created. [13] However, features have been added since the price was originally set that have created a completely new way to discover music, interact socially, and organize digital music libraries, thus creating new value to the platform. Figure 3 presents a timeline for the introduction of these Spotify features. In Swanson's case study on Spotify in 2013, she held a focus group with three non-Spotify users who were described as "casual music listeners", asking their opinion on Spotify. The respondents explained that Spotify was just a fad and inconvenient because there was not always access to Wi-Fi to stream music. This demonstrates that when Spotify was first introduced, consumers did not understand the value of streaming platforms, so the pricing reflected that. The low pricing and freemium model

11 See https://soundcharts.com/blog/music-streaming-rates-payouts
12 See https://www.dittomusic.com/blog/how-much-do-music-streaming-services-pay-musicians
13 See freakonomics.com/podcast/spotify

of Spotify allowed consumers to test out and thus experience the value of Spotify. This thesis aims to quantify this since-added value from features on the platform to understand the extent that streaming platforms can increase their pricing. In this paper, I argue that the customization, uniqueness, and the low degree of transferability of a streaming platform, all reflecting asset specificity, create a high, non-monetary cost to switch from one streaming platform to another.

Figure 3: Spotify Feature Timeline



This thesis has three objectives. First, to identify features of asset specificity within music streaming platforms. These are the features that make the streaming experience unique to its specific user and that involve time investment, whether the user realizes it or not. Second, using these specific features, this paper will measure user loyalty to a specific streaming platform with structural equation modeling. Lastly, the thesis adds a quantitative measure to the value of the streaming platform by using a Bayesian model to estimate individual utilities and understanding the willingness to pay through conjoint analysis (hedonic feature analysis) of the identified features.

Understanding the value that users get from a music streaming platform and thus the price they are willing to pay is important for understanding the business model of the music industry. Music streaming platforms are the center of analysis for this thesis because they restored the revenue gap in the recorded music industry that piracy created. However, there has recently been a lot of conversation concerning if the artists are benefiting from streaming. Ultimately, this paper investigates if there is consumer surplus due to a subscription pricing model that was developed over a decade ago, that could be captured in a new pricing model to restore artists' deadweight loss in revenue. Researchers have worked to measure the effect that streaming has on the industry as a whole, especially pertaining to revenue. There have been many discussions about the development of streaming platforms and user relationships with them, however there is limited work done to quantify these relationships. My thesis is the first to recognize music streaming platforms as a specific asset and use that insight to understand user loyalty and estimate a new pricing model that aims at driving more revenue to the artists.

2. Literature Review

2.1 The Streaming Era

Streaming models are a result of the digital age of entertainment and music streaming has grown exponentially over the years, making it the largest source of music consumption in the US. However, Barker (2018) states that from 1999 to 2017, global music revenues fell to be only around 28% of what they would have been had they kept growing at the current rate with the rest of the economy and music piracy hadn't been introduced. Therefore, there is currently a value gap in the global music industry. Perhaps that value gap comes from the price for digital music being too low. This presents problems for the platforms, the industry, as well as the artists. Molly Hogan (2015) argues that these streaming platforms must charge higher monthly subscription rates in order to provide higher royalty payments to musicians and keep them on the streaming platforms.

Before the streaming era, Smith and Telang (2017) find that the price charged for digital singles was thirty percent too low, while the price for digital albums was set thirty percent too high based on consumer demand. With streaming, people were starting to spend more money on music. Consumers are willing to pay more for streaming subscriptions due to the economics of bundling that allows them to stream all music with no marginal costs as well as the features that provide personalization and sharing (Smith & Telang, 2019). Swanson (2013) finds that the average subscriber spends around $120 per year, while the average download consumer was only spending $60 per year. Courty and Nasiry (2018) develop a model that predicts that a platform should price product attributes instead of product quality when consumers have certain preferences. Now instead of pricing better quality music over lesser quality music, streaming platforms would benefit from pricing based on features in the same way that movie theaters price movies on the showtimes, theater amenities, and screening technologies (Orbach & Einav, 2007). Adomavicius et al. (2019) conducts three laboratory experiments and finds that people are willing to pay more for personalized recommendations. Prey (2017) explains that recently, economics is motivating the platforms to improve their algorithm feature in order to get data on the user to strengthen their relationship with the platform. Thus, the user is understood and recognized in relation to their listening behavior. Similarly, Rayna et al. (2015) finds that personalized pricing based on personalized data is one solution to the loss of revenue from the freemium and pay-what-you-want streaming models. Musical discovery is essential to the development of these platforms and the credibility of the individual algorithms will differentiate the existing platforms (Kjus, 2016).

Dörr et al. (2013) discovers that even music pirates have a positive attitude towards music streaming services because although there is more desire to have free consumption of music, streaming services allow social sharing functions with a new pricing model, making it a good alternative to illegal music consumption. The social feature in streaming platforms also proves important in past research and literature when Sun et al. (2006) studies consumer-to-consumer communication and opinion seeking in the context of online music communities and finds that a strong social network with these users was important for online opinion seekers. Hagen and Luders (2016) explain that music listening and discovery practices are uniquely social and so people rely on friends to help discover new music. The same was true before digital music with the sharing of mixtapes and face to face recommendations (Mesnage et al. 2011). Voida et al. (2005) explains that these users might even be picking and choosing what they share with other users in order to portray a certain identity.

2.2 Asset Specificity

Asset specificity is often studied in business to business relationships, but this paper examines asset specificity in a business to consumer relationship, specifically with streaming platforms and users. Asset specificity refers to investments in assets, physical or human, in a specific relationship that gives one player in the relationship market power (Klein, Crawford, and Alchian 1978). Glauco De Vita (2011) examines the different dimensions of asset specificity and identifies patterns of asset specificity such as the degree of customization that supports the transaction's relationship, the uniqueness of assets, the relationship between the two parties involved, and the transferability of the assets. A streaming platform can be considered a specific asset because if the monthly subscription price increases, the user has to decide between the new, higher price, or the transaction cost that comes from losing all their data like playlists, followers, and saved music. In this sense, the streaming platform holds inelastic demand if the features are valued enough that a user would not want to switch platforms, even if the price increases. Previous literature finds asset specificity to be an important characteristic that drives consumer purchasing. Liang and Huang (1998) found that asset specificity is the most significant construct for inexperienced shoppers when purchasing something in the electronic markets. Suki (2013) examines the relationships of product features, price, and social influence with demand for Smartphones, and found that brand name and social influence were significant in affecting demand. I will use this understanding of asset specificity within business to consumer relationships to understand peoples' demand of and loyalty to music streaming platforms.

2.3 Understanding Consumer Loyalty

Many economists use structural equation modeling (SEM) in their research to test for a measure of consumer loyalty and satisfaction. Chiou & Shen (2005) consider asset specificity as a variable when studying consumer loyalty to internet portal sites. They estimate the relationships of asset specificity, satisfaction and consumer loyalty with SEM. Through surveying users of the internet portal, they conclude that asset specificity makes consumers more loyal because there is less incentive to switch from one internet portal site to another due to invested human assets. Liang and Huang (1998) also use SEM to understand consumer acceptance of products in the electronic market. They find through surveys and modeling that customer acceptance is determined by transaction costs, which are determined by uncertainty and asset specificity of the products. Dörr et al. (2013) collects data from an online questionnaire and uses SEM to measure music pirates' acceptance of Music as a Service. [14] Their model measures the latent variable *Intention to use paid Maas* from survey results measuring *submission of music recommendations, search for music recommendations, desire to own, and flat rate preferences.* Sun et al. (2006) uses SEM to explore the consequences of online word-of-mouth recommendations with surveys having to do with music-related communication but finds that there is no significant relationship between music involvement and online word of mouth. Danckwerts and Kenning (2018) use structural equation modeling to test whether music-based

[14] Streaming platforms

psychological ownership affects streaming users' intention to switch from a platform's free version to its paid version. They find that psychological ownership is largely correlated with users switching to a paid subscription and as users of music streaming services spend time discovering, organizing, listening and sharing music on the platform, they develop a sense of ownership for the particular service.

2.4 Estimating Consumer Willingness to Pay

Conjoint analysis allows researchers to estimate the value that consumers place on certain features and understand consumer willingness to pay (Grover & Babiuch, 2000). Kim et al. (2017) observe Korean and US user preferences and their willingness to pay for individual features on the platforms. Using conjoint analysis, they measure the importance of advertisements, streaming mode, exclusive content, and offline usage. At the time, some platforms offered these features while others did not. Through their research, they find that specifically in the US, the willingness to pay for a music streaming subscription that contained all these features is $14.55, which is higher than what users are currently paying. Weijters, Goedertier and Verstreken (2014) use online conjoint analysis surveys to understand online music consumption, finding that new features increase perceived importance of platforms, especially while recommending methods and social sharing emerge. Through analysis, they find that the audio quality and the business model are the most important features to get consumers to pay for music, while search and social media were the least important platform attributes.[15] I contribute to this literature by specifying features that are most important to focus on to build consumer loyalty, and then estimate the marginal willingness to pay of those features. I investigate, through conjoint analysis, if after a decade of added users and features, the value of the platforms has changed. However, the features I focus on are ones that characterize a streaming platform as a specific asset, not only adding value for the user, but also deterring users from switching platforms.

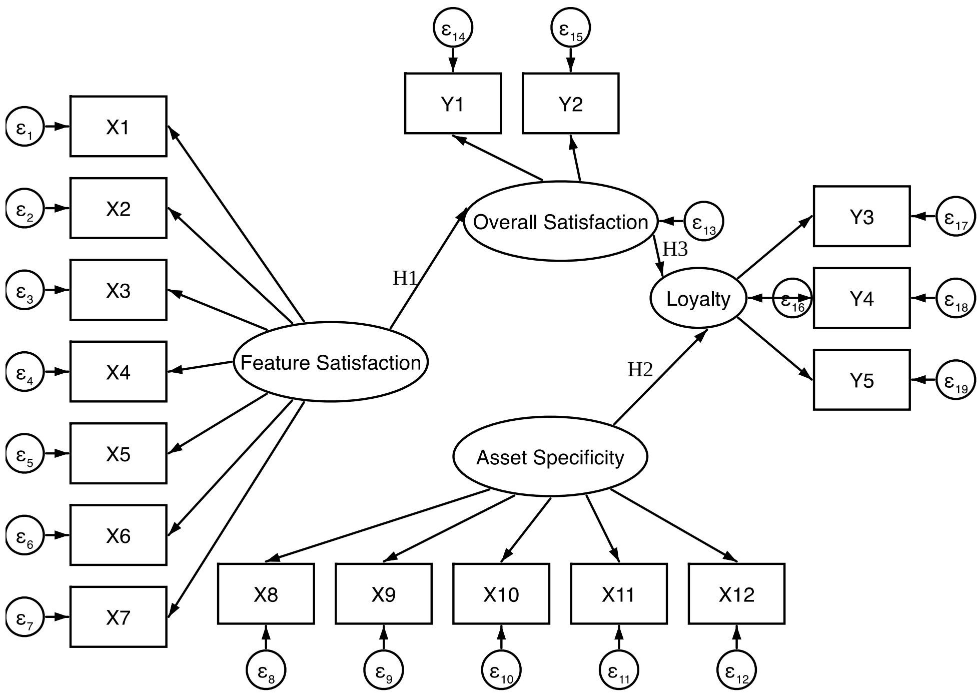
3. Theoretical Framework

I use structural equation modeling and conjoint analysis to model asset specificity of music streaming services that is derived from the features. These are features that require a lot of time and human asset investment from the users. To understand this relationship, I first investigate users' loyalty to the platform and perceived importance of the features. I use structural equation modeling (SEM), a statistical technique that uses factor analysis and multiple regression analysis

[15] Free ad-based, subscription

to analyze the structural relationship between measured variables and latent constructs. Figure 4 presents the structural equation model.

Figure 4: Research Model



SEM is important for this research because I do not have measured variables for asset specificity and consumer loyalty, but I do have empirical data that I collected from surveys. This method allows me to statistically test the theoretical assumptions against the empirical survey data for any causal relationships (Hoe, 2008). The measured variables are data gathered from survey questions, which are meant to capture the perceived demand of the customer, and the unobserved constructs are user satisfaction, asset specificity, and loyalty to a streaming platform. Table 2 presents the hypotheses of the structural equation model.

3.1 Feature Satisfaction & Overall Satisfaction

In the structural equation model, there are feature satisfaction and overall satisfaction. Feature satisfaction refers to customers’ satisfaction to specific features on the streaming platform (Garbarino and Johnson, 1999). Over the years, streaming platforms have introduced new features, such as algorithms, playlists, social interactions, special content, and saved music. Overall satisfaction comes from users’ satisfaction towards the entire platform, including the combined satisfaction of the specific features. The hypothesis is as follows:

H1: Users' feature satisfaction towards a streaming platform will positively affect their overall satisfaction with the streaming platform.

3.2 Asset Specificity and Loyalty Intention

In the case of music streaming platforms as specific assets, users invest time and personalization into the platform that they use, to the point where they may have less incentive to switch to another streaming platform. This is because users have invested time into creating playlists and understanding the interface, as well as relying on their followers and curated music selections to get recommendations for music. [16] If users were to switch accounts, they would lose all the music they have saved, all the playlists they have created, and their specific algorithm on their account that has the ability to curate their music tastes to them. Similarly, if they build relationships to other users on the platform and switch platforms, they will lose the value from sharing music with these users on the specific platform. There are low transaction costs while using a platform, but there seem to be high switching costs that would follow. Therefore, the hypothesis is:

H2: users' asset specificity with a streaming platform will positively affect their loyalty intention toward the streaming platform.[17]

3.3 Overall Satisfaction and Loyalty Intention

Overall satisfaction will affect users' behavior towards purchasing the product, or in this case, subscription. Satisfied customers will continue to renew their subscription. Thus, the last hypothesis is:

[16] Based on the algorithm

[17] This creates adjacent complementarity, the concept that the greater current consumption raises future consumption (Becker & Murphy, 1998)

H3: users' overall satisfaction with a streaming platform will positively affect their loyalty intention.

Table 2: SEM Hypotheses

Causal path	Hypothesis	Expected sign
Feature satisfaction → overall satisfaction	H1: users' satisfaction towards features of a streaming platform will positively affect their overall satisfaction with the streaming platform	+
Asset specificity → loyalty intention	H2: users' asset specificity with a streaming platform will positively affect their loyalty intention toward the streaming platform	+
Overall satisfaction → loyalty intention	H3: users' overall satisfaction with a streaming platform will positively affect their loyalty intention	+

This model allows me to test how loyal a user is to their specific streaming platform based on their human asset and time investment in the platform and its features as well as overall satisfaction. By testing the different hypotheses that relate to the paths, this paper will estimate if there are causal relationships between feature satisfaction, overall satisfaction, asset specificity and loyalty intention. If asset specificity is positively correlated to loyalty intention, then that could mean that users face a high switching cost if they were to switch platforms, thus an increase in price may have a smaller effect on market share.

3.4 Measuring Marginal Willingness To Pay

The structural equation modelling framework uses stated preferences to understand user loyalty, whereas the conjoint analysis framework uses revealed preferences to understand feature importance and willingness to pay. Conjoint analysis (hedonic feature analysis) measures consumer preferences for comparable attributes, in this case, features. Conjoint analysis is a statistical technique that is commonly used to value a combination of product features. The advantage of using conjoint analysis for this research is that platform features are presented together, requiring users to make tradeoffs between features as they would if they were actually choosing a platform to use and considering their options in relation to price. Specifically, this experiment uses discrete choice analysis, which is somewhat different from traditional conjoint analysis and is considered more general and consistent with economic demand theory (Louviere, Flynn & Carson, 2010). Discrete choice experiments (DCE) take into account human behavior with multiple choice comparisons using random utility theory (McFadden, 1974). Discrete choice experimentation allows researchers to understand user tradeoffs between attributes and price, without directly asking respondents what they are willing to pay (Grutters et al., 2008). It is important to use DCE, an indirect measure, for this research because users are familiar with the product, so when asked what they are willing to pay, they would be inclined to answer what price they are already paying. However, a person derives utility from a choice alternative, in this case, a platform's feature. By estimating these utilities, I will indirectly observe and estimate a marginal willingness to pay for the platform as a whole. Since there have been added features that allow personalization and users have a better understanding of the value of a streaming platform than when subscriptions were originally priced at $9.99, I hypothesize that users are willing to pay more than they currently are for a music streaming subscription.

4. Data

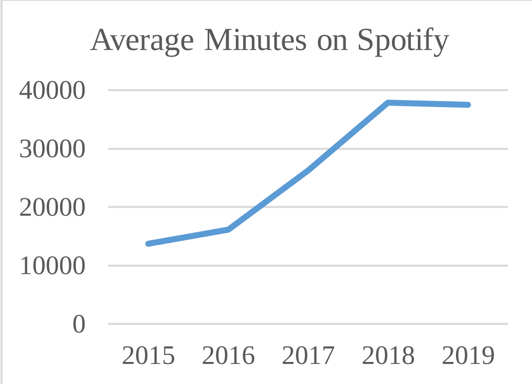
The United States has experienced some of the largest growth in streaming platform users, with 43% of U.S. consumers subscribing to an audio streaming service and 61.1 million paid music streaming subscribers in 2019 (Rain News, 2020). In 2018, millennials made up 40% of the user population with a music streaming service subscription and ages eighteen to twenty-four represented one of the largest shares of Spotify's monthly active users worldwide (Verto Analytics, 2018). To understand consumer loyalty to and willingness to pay for music streaming platforms, I developed an online survey. A survey was required for my research because there is limited public data available on user behavior with music streaming platforms. The data available is annual snapshots of aggregate user data such as user numbers and revenue amounts per year, or very costly to obtain, such as the Nielsen survey data on their Nielsen Music 360 report. The survey was created on a platform called Conjoint.ly, using survey items taken and redeveloped from previous research; some that studied user loyalty and others that estimated willingness to pay. This was done in order to avoid any validity problems. Tables A1 and A2 in the appendix present all the survey items as well as the sources they were taken from. Prior to sending out the survey, I received IRB approval as well as Duke Economics department funding in order to offer compensation to respondents for completion and collect enough responses for statistical analysis. In order to understand users' relationship with streaming platforms, I first surveyed a small group of college students. This allowed me to identify which features are most important to users and then use those results to survey a larger group of users in the United States. I developed the survey to measure user loyalty as well as estimate the importance of and willingness to pay for different features on the platform.

4.1 Duke Student User Sample

To understand which features are most important and personalized to users, I surveyed a small portion of Duke's student population who use Spotify. I surveyed students who use Spotify, as opposed to other streaming platforms, because Spotify releases user-specific data to each user every year. This report provides personalized user data on listening patterns, which include how many minutes the user has spent on the platform every year since 2015. To collect this data, as well as feature preferences on the platform, I sent out a survey on social messaging platforms like GroupMe and posted on Facebook. Thirty students responded to the survey and provided their listening data from the years 2015 to 2019. [18] While this data is not representative of entire streaming platform user base, I was able to collect qualitative numbers to represent the time investment of respondents in the past five years in relation to their preferences on the platform's features. This allowed me to estimate their platform preferences as well as their platform use to analyze how time investment in the platform affects user preferences at a basic level.

[18] The majority of these Duke students were seniors, ages 21-23.

Figure 5: Duke Student User Sample Summary



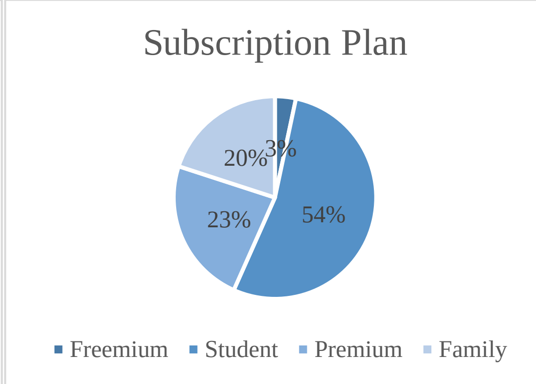
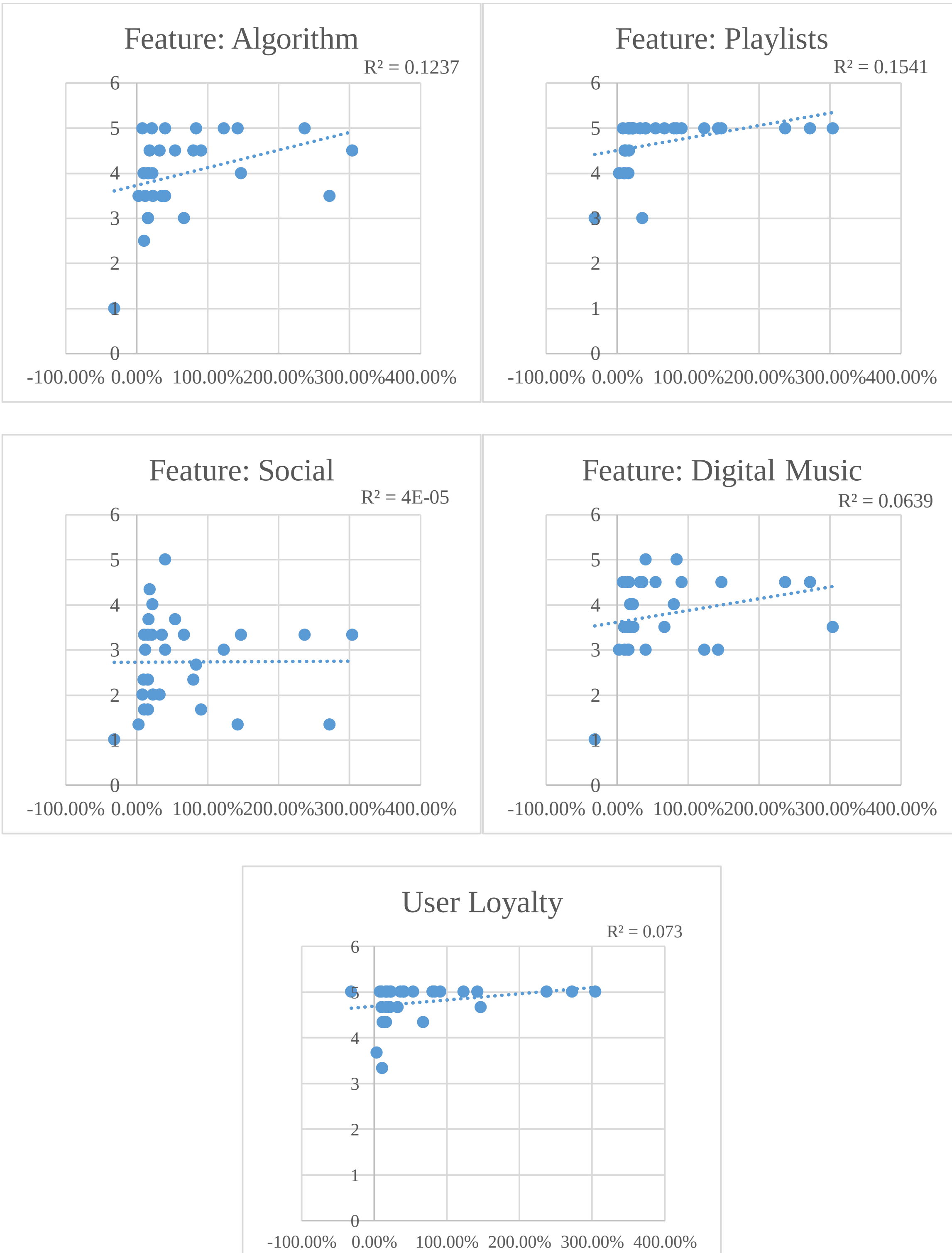


Figure 4 shows that the respondents' average yearly minutes spent, or time invested, on Spotify since 2015 has increased and then steadied out in the past year. Even if they are passively using the platform, the act of listening to music and interacting with the music is a time investment into the platform's algorithm. As shown in Figure 5, the majority of the respondents subscribe to the student plan, which is $4.99 a month, while the minority of respondents use the free Spotify plan. While this is not representative of a wider population, it is interesting to note that within this student population, the free ad-based subscription is not favorable. The preliminary survey revealed that the most important features on a streaming platform are curated music suggestions through algorithms, access to others' playlists and ability to create own playlist, platform interface, social aspects, and price.

Additionally, I plotted the users' growth in streaming minutes on Spotify for the last five years with results from the survey regarding importance of different streaming features. These plots are shown in Figure 6. The basic plots of the data show that there is a positive trend between percent growth in streaming use and the algorithm feature, playlist feature, and digital music feature, while there was no significant trend between percent growth and the social feature. This initial data supports my hypothesis of asset specificity within a streaming platform because as a user spends more time on their respective platform, they strengthen their algorithm, invest more effort into creating playlists, and grow their digital music library. Thus, these features become important to them as they use the platform more. Similarly, there is a positive trend between percent growth and measurement of user loyalty from the survey. This also supports my hypothesis that as users spend more time on a platform, they become more loyal to that platform, possibly due to these asset specific features. Based on these findings, I constructed a survey with a larger, more extensive respondent base to understand how these features affect user loyalty and what the willingness to pay for these features are.

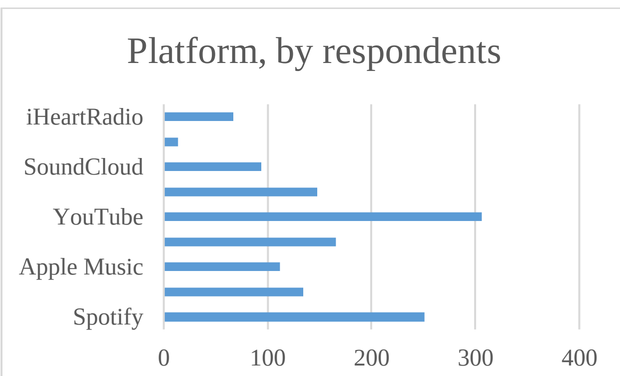
Figure 6: Duke Student User Sample minutes on Spotify ratios



4.2 U.S. User Sample

I created another survey on Conjoint.ly to send out on Amazon's Mechanical Turk, a crowdsourcing website operated under Amazon Web Services. The survey was posted and collected 700 responses from users of music streaming platforms in the United States. Each respondent was paid $0.50 to complete the survey. Instead of focusing on only Spotify, the survey asked questions about all music streaming platform use. For the conjoint analysis, it is important to have attributes and prices from different comparable platforms, not exclusively Spotify. From the 700 respondents, 446 adequately took the survey, which I filtered by how long they spent on each question in comparison to the average time spent on the survey, to determine if they read through all the choices. The survey platform automatically filtered out responses where respondents did not look through all the options presented, which is important for the portion of the survey that presents conjoint analysis choice cards. This number of respondents well exceeds the proposed critical sample size of 200 for structural equation modeling and conjoint analysis (Garver & Mentzer, 1999; Hoelter, 1983).

Figure 7



71% of respondents were between the ages of 26 and 49, 15% were between 18 and 25, 12% between 50 and 65, and 2% over the age of 65. These age statistics mirror the statistics for US users. Figure 7 shows the number of respondents per streaming platform. 48% of respondents have the free ad-based subscription, 23% of respondents pay $4.99 per month, 21% of respondents pay $9.99 per month, 7% of respondents pay $14.99 per month, and 1% of respondents pay $19.99 per month. On average, respondents subscribe to two to three music streaming platforms.

The first part of the survey measures user loyalty. The questions come from previous economic research to understand loyalty of internet platforms and portals. The survey asks about feature satisfaction, asset specificity, overall satisfaction, and loyalty intention with questions answered on a 5-point Likert Scale. Table A1 in the appendix presents all the statements and sources that are given in this part of the survey, and respondents respond on a 5-point scale with 1 being "completely disagree" and 5 being "completely agree". Loyalty is measured with these survey responses and latent variables using structural equation modeling.

The second part of the survey estimates which features are most significant and their value using conjoint analysis. Conjoint analysis quantifies user preferences for features, which can then be used to estimate a marginal willingness to pay. The survey was created on Conjoint.ly, which creates surveys and reports to specifically measure this relative importance of attributes and the marginal willingness to pay. Participants were asked to choose between three profile cards at a time, which have different features on them. [19] The user respondents choose which choice card they prefer, indirectly choosing which features are most important to them in relation to the price. The features presented in the choice cards are presented in Table A2 in the appendix. The choice cards specify three possible combinations with different levels of the features of a product. The choice of "none" is also given when none of the options is preferred. The features in the analysis are the features highlighted by the student survey group as the most important features: algorithm, social, playlist, and offline listening.

4.2.1 Algorithm Feature

The algorithm feature is important because it uses user data to personalize the listening experience. Streaming platforms keep track of songs the user likes and saves and uses that data to create playlists with similar artists, songs, and genres, to appeal to the specific user. The more a user utilizes a platform, the more data the platform has on them, and the music discovery becomes more specific and personalized. The more personalized a streaming platform becomes, the less likely users will be to switch to another platform and these streaming services will have more ability to raise prices for established customers (Kreuger, 2019). This introduces a new transaction cost, since the user invests time and effort to improve the algorithm on their account.

4.2.2 Social Feature

Interactive streaming platforms also allow users to follow their friends and vice versa. This is important, especially for music discovery and sharing music. Users may not want to

[19] See Figure A1 in the appendix

switch platforms because of the added cost of losing their followers or not being able to follow certain people. The social feature also acts as a discovery feature for users. The asset specificity comes from most users only being on one platform and thus losing these followings if users switch.

4.2.3 Playlist Feature

Playlists, both automatic and curated, are an important feature for music discovery and organization. They help people discover music based on certain attributes to the music. Over the years, playlisting has become an important marketing tool for musicians to be discovered, so much so that curators of popular playlists charge money to musicians who want to be added on their playlists. Spotify reported in 2018 that 31% of its listening time on the platform occurred through playlists, which was a 30% increase from two years earlier (Spotify Technology, 2018). For a user, the human curation and personalization of a playlist introduces asset specificity because the playlist is only on one platform. On the curator side, this introduces asset specificity due the transaction cost of losing all your followers and thus the playlist importance from switching platforms.

4.2.4 Saved Music Library

Interactive, on-demand platforms allow you to save music in your library, which also allows you to listen offline. A user who subscribes to a particular platform for many years will most likely have a lot of music saved. The act of switching all of this music to another platform would take a good amount of time for a longstanding user, thus making these libraries asset specific. A switching cost arises from going from one platform to another and losing all the saved music.

4.2.5 Price

Price identifies the amount of money that consumers are willing to pay each month for a subscription on the platform. Currently, all of the popular interactive platforms have the same pricing tiers of free (with advertisements), $4.99 for students, $9.99, and $14.99 for families. Tidal is the one platform that offers a subscription price at $19.99.

5. Empirical Methodology

5.1 Structural Equation Modeling

To understand and test the relationships, I build a structural equation model to measure user loyalty, which can be seen in Figure 7. I estimate the relationship model using maximum likelihood method, since the data shows no significant kurtosis (Bollen, 1989). The survey questions that I use to estimate the latent variables are shown in Table 4. Chiou and Shen (2005) use a similar method of testing satisfaction and asset specificity on users' loyalty toward internet portal sites.

I use confirmatory factor analysis (CFA) to test the construct validity and evaluate how well the latent variables are measured by the observed, survey variables. The overall fit of the structural equation model is $X^2_{(116)} = 1015.154$, $p = 0.000$, RMSEA = 0.132, CFI = 0.702, TLI = 0.651, SRMR = 0.185, CD = 0.976. However, these statistics are not satisfactory and prove it to be a poor fit. This poor model fit might be due to the lack of stated correlations between similar survey item constructs. There is correlation and covariance between survey constructs of the latent variable *feature satisfaction* as well and the survey constructs of the latent variable *asset specificity*, since both pertain to a specific feature of the platform. For that reason, I add covariance connections to the corresponding feature constructs, as well as a path connecting the latent variables *feature satisfaction* and *asset specificity*. This path is justifiable because the first set of questions asks about specific features and pertains to the following questions that ask about asset specificity due to these same features. Thus, I hypothesize that there is a positive correlation between *feature satisfaction* and *asset specificity*. Similarly, the constructs for the latent variable *overall satisfaction* are highly correlated to the constructs for the latent variable *loyalty*. I also add covariance connections between these corresponding constructs. The new model with the added connections and path can be seen in Figure 8. [20]

After the model was updated, the goodness of fit statistics show that the new model provides a better fit. The new overall fit of the structural equation model is RMSEA = 0.092, CFI = 0.868, TLI = 0.831, SRMR = 0.093, CD = 0.802. The RMSEA which measures the difference between the observed and estimated covariance matrices per degree of freedom (Steiger, 1990) represents a moderate fit at .092 (Hoe, 2008). Additionally, the CFI and TLI are close to 0.9 and SRMR is close to 0 while the CD is close to 1 representing adequate fit of the structural equation model (Stata). In the table, the p-values for all the standardized factor loadings are below the 0.005 threshold and are thus statistically significant. A measurement test of the Cronbach's α tests the reliability of the items used in the survey (Likert, 1932). As seen in Table 4, the α coefficients

[20] The green paths represent correlation connections

for all the items are greater than 0.80 and all similar, which is evidence of reliable items (Nunnally. 1978) Additionally, the model is tested for undimensionality, which checks that there is only one construct underlying a set of items (Hoe, 2008). Principle component analysis measures each variable's eigenvalue to determine undimensionality (Germain, Droge and Daugherty, 1994). Only the first eigenvalue is greater than one for all of the latent measures, which can be seen in Table 3, so it is reasonable to accept undimensionality of this model (Hoe, 2008). Furthermore, none of the correlations between the latent variables are one, which is one of the most common test of discriminant validity (Smith and Barclay, 1997).

Table 3: Dimensionality of SEM

Latent Measure	***Component***	***Eigenvalue***	***Proportion***	***Cumulative***
Feature Satisfaction	1	6.48039	0.9258	0.9258
	2	0.351964	0.0503	0.9761
	3	0.060164	0.0086	0.9846
	4	0.0442173	0.0063	0.9910
	5	0.0268549	0.0038	0.9948
	6	0.0199114	0.0028	0.9976
	7	0.0165022	0.0024	1.0000
Asset Specificity	1	4.72755	0.9455	0.9455
	2	0.197035	0.0394	0.9849
	3	0.038723	0.0077	0.9927
	4	0.0267186	0.0053	0.9980
	5	0.00996985	0.0020	1.0000
Overall Satisfaction	1	1.99255	0.9963	0.9963
	2	0.00744903	0.0037	1.0000
Loyalty	1	2.8648	0.9549	0.9549
	2	0.0944728	0.0315	0.9864
	3	0.0407251	0.0136	1.0000

Figure 8: Updated SEM

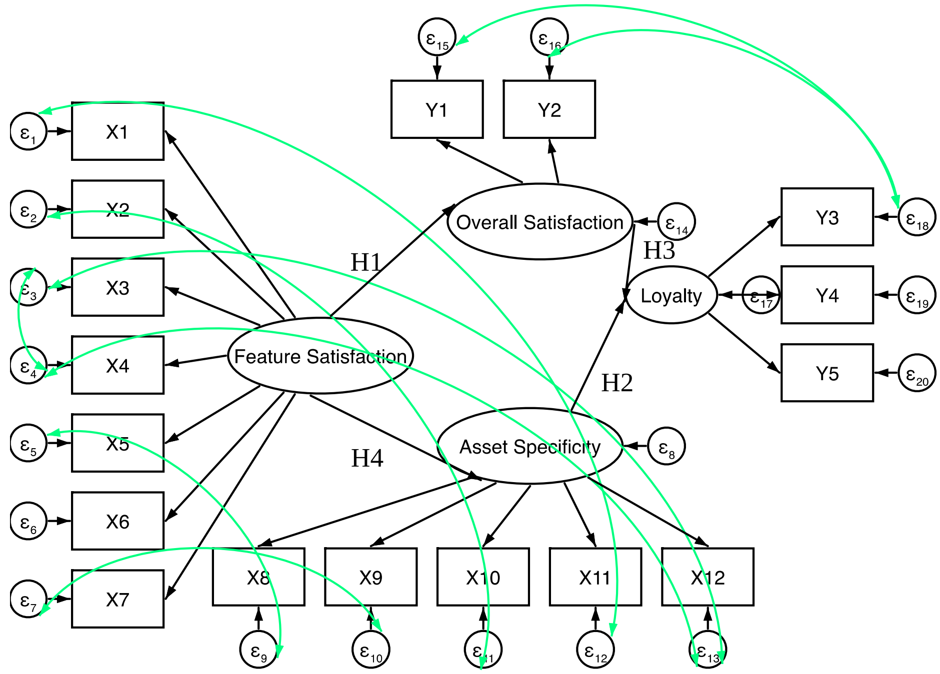


Table 4: SEM constructs, coefficients, and validity

Constructs	Standardized	z-value	Cronbach's α
Feature Satisfaction			
X1: I tend to seek out music with [Spotify's] suggested music for me based on my listening habits.	1 (constrained)		0.9928
X2: Using and creating playlists are valuable	0.7698058	8.18	0.9928
X3: I tend to consult the users I follow regarding what music I should listen to	1.171534	8.47	0.9935
X4: Following people on the streaming platform is valuable	1.005324	7.58	0.9932
X5: I would be sad if I lost my digital music library to technical issues	0.7353171	6.62	0.9928
X6: I seek out exclusive content not available on other streaming services, for example, exclusively released albums and video content	1.2605	8.51	0.9932
X7: My decision to use a platform is strongly linked to the platform's interface.	0.7503948	7.41	0.9928
Asset Specificity			
X8: If I switch to other music streaming platforms, I have to spend a large amount of time to set up my digital music library	0.9755695	10.66	0.9928
X9: If I switch to other music streaming platforms, I have to spend a large amount of time to understand how to use the platform	0.9619265	11.00	0.9930

X10: If I switch to another music streaming platform, I have to spend a large amount of time to set up and find playlists	1.078146	14.05	0.9928
X11: If I switch to another music streaming platform, I have to spend a large amount of time setting up the service to understand my music taste.	0.9951628	12.17	0.9928
X12: If I switch to another music streaming platform, I have to spend a large amount of time following people	0.8763511	9.01	0.9936
Overall Satisfaction			
Y1: I am happy about my decision to use Spotify	1 (constrained)		0.9931
Y2: Overall, I am very satisfied with Spotify	1.02635	14.71	0.9931
Loyalty			
Y3: If I have to do it over again, I would choose Spotify	1 (constrained)		0.9931
Y4: I consider myself to be a loyal patron of Spotify	0.1856324	10.29	0.9933
Y5: If Spotify raised their price by a small margin, I would continue to use Spotify	1.56578	9.38	0.9928

*This multiple factor measurement model uses the measured variables *X* to represent the responses having to do with specific features on streaming platforms, specifically the features that qualify the platform as a specific asset. The measured variables *Y*, more general responses having to do with users' inclination towards a streaming platform.

5.2 Hierarchical Bayesian Multinomial Logit Model of Choice

After conducting a survey using conjoint analysis, specifically discrete choice experimentation (McFadden, 1974; Louviere, Flynn & Carson, 2010), I use a hierarchical Bayesian multinomial logit model of choice to estimate users' marginal willingness to pay for each feature. I use hierarchical Bayesian modelling because it is a type of modeling that estimates utilities for individuals, instead of for a market as a whole (Conjoint.ly). This statistical technique is used to make inferences about a population based on individual observations, in this case, streaming users, instead of averaging the aggregate response. The benefits to using hierarchical Bayesian modelling are the coefficients measuring individual utility help account for heterogeneity in the streaming market and more attributes and levels can be estimated in conjoint analysis with smaller amounts of data collected from each respondent. Table A2 in the appendix presents all the features in which marginal willingness to pay is measured using survey conjoint analysis. The survey platform, Conjoint.ly, specializes in measuring willingness to pay through conjoint analysis. The estimations are based off of discrete choice experiments, which rely on random utility theory. Discrete choice experiments have individuals choose between a group of alternatives, on the basis that they are choosing to maximize their personal utility. These choices correspond with utility levels, which are combinations of the relative importance of the attributes, in this case, platform features (García, 2005). Random utility theory explains the individual's process of choosing from a group of available alternatives by assuming that the latent utility is made up by a systematic, measured component, and a random component.[21] Essentially, the marginal willingness to pay is the marginal rate of substitution of feature for price.

$$U_{in} = V_{in} + \varepsilon_{in}$$

Where U_{in} is the latent utility variable that individual n identifies with the choice alternative i, V_{in} is the systematic, measured component of utility that individual n identifies with the choice alternative i and ε_{in} is the random component that is associated with individual n and the choice alternative i.

Random utility theory measures the probability that individual n will choose choice alternative i, from the competing alternatives:

$P(i|C_n) = P\left[(V_{in} + \varepsilon_{in}) > Max\left(V_{jn} + \varepsilon_{jn}\right)\right]$[22], for all j options in choice set C_n.

The relative importance of attributes and value of measures is estimated using a hierarchal Bayesian multinomial logit model of choice. This is done by calculating attribute importance and partworth utilities by taking coefficients from the estimated model and linearly transforming them. V_{in} can be represented as a linear function of features, such as price, algorithm, playlisting, social, and downloaded music, as follows.

$$V_{in} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \beta_{nkl} z_{ikl}$$

Where β_{nkl} represents a partworth of level l of attribute k for individual n. That means the partial utility that a user assigns to certain attribute level, or feature, which is estimated

21 The random component helps take into account unidentified factors that impact human decisions, making humans imperfect measurement devices.

22 The probability that individual n chooses option i from the choice set C_n equals the probability that the measured and random components that individual n chooses option i are larger than the measured and random components of all other components competing with option i.

through the survey. z_{ikl} is a binary variable that equals 1 for alternative i with level l of attribute k.

The probability of individual n choosing alternative i from the set of alternatives j is

$$P_{in} = \frac{e^{V_{in}}}{\sum_{j' \in J} e^{v_{ij'}}}.$$

This utility function allows me to calculate attribute importance as the difference of maximum and minimum partworths of a given attribute divided by the sum of partworth of each attribute. I derive willingness to pay from the partworth values that are estimated from hierarchical Bayesian analysis (Louviere, Flynn & Carson, 2010). To compute willingness to pay, only one partworth value is assigned to each attribute in order to create a linear functional form of utility. [23] Willingness to pay is then estimated by dividing the partworth value of a product attribute by the price.

$$wtp_{nk} = -\frac{\beta_{nk}}{\beta_{np}}$$

Where wtp_{nk} is individual $n's$ willingness to pay for feature k, β_{nk} is individual $n's$ partworth value for feature k, and β_{np} is individual $n's$ partworth value for price. The negative sign reflects that a higher price correlates to lower value, and thus correctly reflect the tradeoffs between feature levels.

6. Results

6.1 *Results from Structural Equation Modeling*

The effect of feature satisfaction on overall satisfaction of a music streaming platform is significant (γ = 0.38, p < 0.000). This reveals that satisfaction of a platform's features is somewhat important to overall satisfaction of the platform. The hypothesis H1 is supported by the data. The effect of asset specificity on user loyalty is significant in the positive direction (γ = 0.15, p < 0.000). While this is a marginal effect, since the standardized path is less than 0.3 (Chin, 1998), the positive coefficient shows that a users' investment to the specific asset of a

[23] The other feature level is the baseline

streaming platform will increase that user's loyalty towards the platform. Therefore, the hypothesis H2 is supported by the data. The effect of feature satisfaction on asset specificity, which was predicted in the new model, is positive and significant ((γ = 0.89, p < 0.000). This tells us that users' satisfaction towards features will make the platform more of a specific asset for the user. The new hypothesis H4 is supported by the data. Lastly, as expected, overall satisfaction positively affects user loyalty intention significantly (γ = 0.46, p < 0.000). The hypothesis H3 is supported by the data. Figures A2 and A3 in the appendix lay out these relationships from the SEM. The idea that asset specificity within streaming platform features makes consumers more loyal to the platform is similar to the findings of Chiou and Shen (2005) that asset specificity within online portals makes consumers more loyal because there is less of an incentive to switch from one portal to another because of human investment.

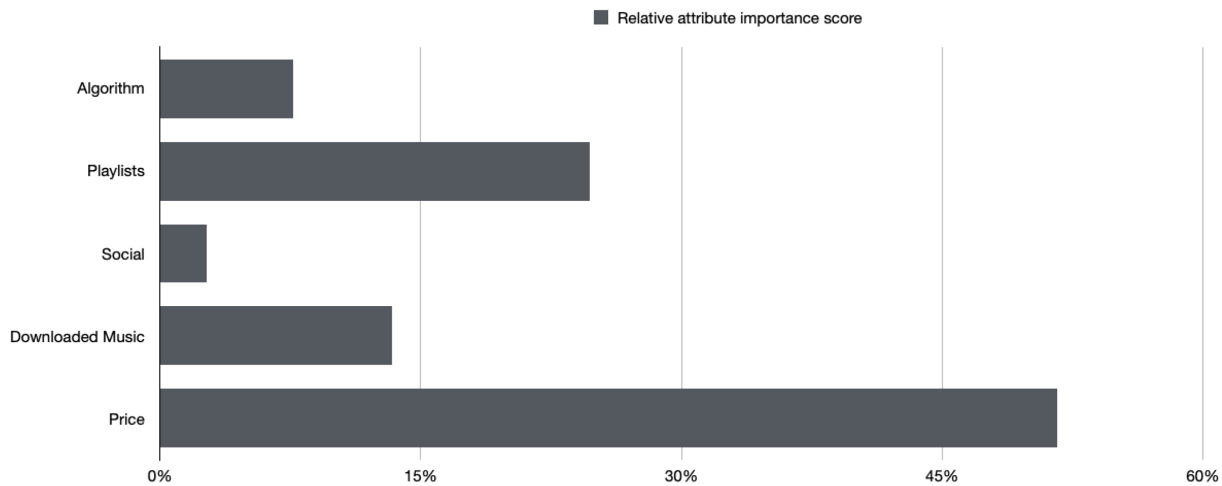
Table 5:Updated hypotheses

Causal path	Hypothesis	Expected sign	Standardized structural coefficient	z	p
Feature satisfaction → overall satisfaction	H1: users' satisfaction towards features of a streaming platform will positively affect their overall satisfaction with the streaming platform	+	0.3795909	5.56	0.000
Asset specificity → loyalty intention	H2: users' asset specificity with a streaming platform will positively affect their loyalty intention toward the streaming platform	+	0.1471817	5.69	0.000
Overall satisfaction → loyalty intention	H3: users' overall satisfaction with a streaming platform will positively affect their loyalty intention	+	0.4573848	8.21	0.000
Feature satisfaction → asset specificity	H4: users' satisfaction towards features of a streaming platform will positively affect the asset specificity of the platform.	+	0.8891068	7.97	0.000

6.2 *Results from Conjoint Analysis*

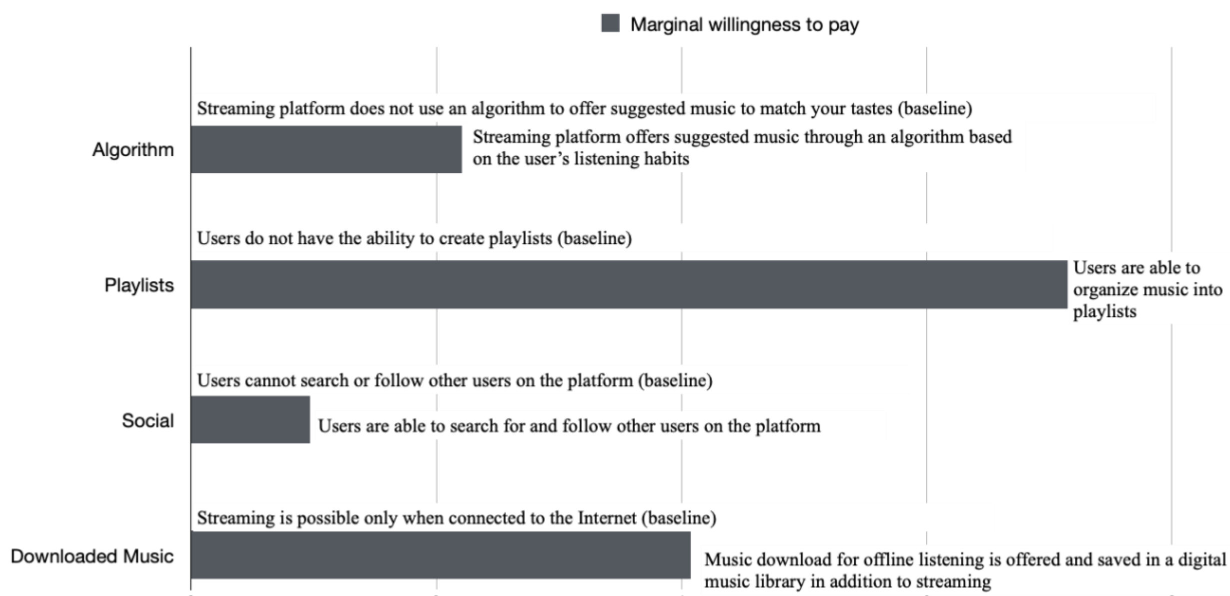
The structural equation modeling confirms that these features are important in affecting consumer loyalty. Next, I use a hierarchical Bayesian multinomial logit model to estimate the importance and value of each feature on Conjoint.ly. McFadden's pseudo R^2 is found to be 0.62, which reports the model as medium goodness of fit (McFadden, 1974). Higher values of Pseudo R-Square are linked with greater price sensitivity (Louviere & Islam, 2006). Based on the respondents, price is the most important attribute of a streaming platform, followed by the ability to make and share playlists. The least important attribute of a streaming platform is the social aspect, allowing users to follow other users, shown in Figure 9. The relative importance of these features confirms the findings of Danckwerts and Kenning (2018) that psychological ownership from discovering, organizing, listening, and sharing of music is largely correlated with consumers paying for music,

Figure 9 – Relative importance by attribute



This is an interesting finding, since Dörr et al. (2013) found social recommendations to be an important aspect to get music pirates to switch to streaming. Respondents' MWTP for each attribute is calculated with similar partworth estimates including price on Conjoint.ly.

Figure 10 - Marginal willingness to pay



The marginal willingness to pay for the algorithm feature is $2.21, playlist feature is $7.15, social feature is $0.97, and downloaded music is $4.07, as seen in Figure 10. These marginal willingness to pay measures are relative to the baseline, which in this case is not having the feature. To interpret these results, users are willing to pay $2.21 more for a platform with the algorithm feature, $7.15 more for a platform with ability to make and find playlists on a platform, $0.97 more to interact socially on a platform, and $4.07 more for the ability to download music and listen to it offline on a platform. The utility gained from all of the improved features is greater than the utility gained from the base figures, which represents that the respondents prefer the improved platform. Additionally, the utility gained from the first level of the reservation price is greater than the utility gained from the second level of the reservation price, thus the respondents are willing to pay for the improved attributes and the willingness to pay for the platform is at least the compound marginal willingness to pay for the features (Patrakis, 2015). Thus, users are willing to pay at least $14.40 per month for a streaming platform that includes all of these features. This price is higher than the current individual music streaming subscription priced at $9.99 per month for most streaming platforms. [24]

7. Discussion

This study examines music streaming platforms as specific assets to the user. The asset specificity is characterized by the algorithm, playlisting, social, and downloaded music features on the platform, which are improved and strengthened based on the user's time and utilization investment. To understand these features and how they shape the asset specificity of a platform, I use consumer data that I collect through surveys to first observe the causal relationship between these features and consumer loyalty to a platform with structural equation modeling. Then, I use conjoint analysis to estimate users' marginal willingness to pay for these features.

With a small sample population, there seems to be a positive trend between time spent on a streaming platform and the importance of certain features on that platform. The results of the structural equation modeling show that satisfaction with certain features, specifically algorithm, playlisting, and downloaded music, on a platform is very important to overall satisfaction of a streaming platform and thus, user loyalty. Streaming platforms should focus on these features to increase consumer loyalty. Similarly, those features have a positive effect on asset specificity, which conveys that the users found that there would be a large time-related switching cost from

[24] Tidal is the only platform that offers a higher priced platform at $19.99 for premium service

having to build up those features again. The effect of asset specificity on user loyalty is less notable, however still positive. To strengthen user loyalty and create demand inelasticity, streaming platforms should encourage users to build and establish these specific features such as a strengthened user-unique algorithm and a large library of playlists and downloaded music. Users find value in these features when they invest time and utilization into them, however they would lose all this value if they switch to another streaming platform, therefore making the platform a specific asset. This supports both Adomavicius et al. (2019) and Rayna et al. (2015) findings that people are willing to pay more for personalization, making it essential to increase platform revenue.

Additionally, while conjoint analysis shows that price is the most important attribute of a streaming platform to users, the compound willingness to pay of all the features totaled $14.40 per month. This price is higher than the price streaming platforms are currently charging for a monthly subscription. This is similar to the price that Kim et al. (2017) found when conducting conjoint analysis and measuring willingness to pay for a completely different set of features. Playlisting and ability to download music are the most important features of a streaming platform, while social following is the least important feature of a streaming platform, for both the student and U.S. respondents. The unimportance of the social feature may be due to the social pressures and intimacy that have to do with sharing music (Voida et al., 2005).

Daniel Ek argues that his streaming platform, Spotify, cannot raise its price to more than $10 because people are barely willing to pay that much, and the alternative is pirating music. Another argument is that if one platform raises their subscription price, users will switch to a competing platform. The purpose of this thesis and the results from the survey data show that users are already willing to pay more than the current price for streaming subscriptions based on the specific features. Moreover, I suggest that streaming platforms have the ability to raise their prices because the features make them specific assets to the extent that they build consumer loyalty and gain market power over time. To address the concern of driving away new users, platforms could create a pricing model that allows for a free, or low-priced, streaming period, which expires after users invest time and human assets into the platform. Uniform pricing of music leads to lower than optimal profits since these digital firms are not price discriminating as much as they can (Shiller and Waldfogel, 2011). If streaming platforms would begin to raise their prices based on user loyalty and willingness to pay, it would in turn increase revenue that artists make from their royalty agreements, as well as overall revenue in the industry as a whole.

Some limitations of this research must be considered. Firstly, since the data collected is from surveys, it is not perfect representation. The respondents are all from the U.S., where streaming has been around for over a decade and there is market competition with platforms. To understand users' demand more thoroughly, similar research should be done in other countries. Also, I compensated users for survey completion on Mechanical Turk, which may have led to a specific type of respondent. Further research should gather survey responses from different forms of surveying and without compensation. Additionally, the conjoint analysis choice sets may present some implications if respondents started to lose focus as they were completing the survey, especially with the "no choice" option present (Wlömart and Eggers, 2016). This, as well as the fact that this analysis uses revealed preferences instead of stated preferences, introduces random response error. Future research would benefit from additional robustness checks to strengthen the model as well as more exploration into the presence of multicollinearity. Secondly, there is an additive assumption with the conjoint analysis, which states overall willingness to pay for the platform with compounding the marginal willingness to pay for features. There are disputes among economists about this assumption, which poses an opportunity for more research. Lastly, new technology has been introduced to help users switch from one streaming platform to another, by converting the digital music library between platforms. While this technology is not widely used, it presents a solution to the switching cost and thus the asset specificity of the platforms. This study shows that streaming platforms have characteristics of asset specificity that allows them to increase the price of the subscription. This increase in subscription price would not only benefit the platform, but also the artists and the entire industry.

8. Conclusion

In the past decade, streaming has transformed the landscape of the entertainment industry. Streaming in music came at a time when piracy was taking a negative toll on the industry's revenue. To fix this problem, streaming platforms, starting with Spotify, offered a monthly subscription to stream unlimited songs for as high as $10 per month. As the platforms developed, features were added to give users more personalization in the streaming experience. Users can create and share playlists of music that they put together, build a library of downloaded songs and follow other users on the platform to share and discover their music. Additionally, the more time and human capital that a user invests in the streaming platform, the better the algorithm understands what kind of music they enjoy. This enables the platform to personalize the experience even more by recommending artists and curating music discovery based on the user's algorithm. These features create asset specificity within the streaming platforms, meaning the features are improved and strengthened to the users' liking based on the user's time and utilization investment. This thesis shows how asset specificity, which is usually considered a hold up problem in business to business enterprises, can also be a consumer problem and is creating market power within these platforms in an otherwise competitive market.

Through consumer surveys, I collect data to examine user loyalty to streaming platforms and estimate what users are willing to pay for a subscription based on the asset specificity of the features. A structural equation model of survey data shows that feature satisfaction positively affects both asset specificity of and overall satisfaction with streaming platforms, strengthening user loyalty. Specifically, the more a user invests in building up their algorithm, playlists, and downloaded music libraries, the more satisfied and loyal they are to the overall platform. This verifies that customization, uniqueness, and low degree of transferability of these features correlate to user loyalty, giving the platform market power to raise subscription price and thus increasing the revenue that artists on the platform would receive. To understand what this raise in subscription price could look like, I use conjoint analysis (hedonic feature analysis) with a hierarchical Bayesian multinomial logit model to estimate users' willingness to pay on an individual level to then make inferences about the population. I collect 446 consumer survey responses using discrete choice experimentation, where respondents choose between a group of alternative streaming platform options. I estimate that users are willing to pay $14.40 per month for a music streaming platform that offers algorithm playlist and social features, with the ability to download music. This subscription price is 144% higher than what most streaming platforms, including Spotify and Apple Music, are charging.

Users are already willing to pay more than the current price for music streaming platform subscriptions. Additionally, platforms can increase their subscription price among current users because the personalized features within the platforms have made them specific assets on a business to consumer level. An increase of the subscription price would ultimately lead to higher royalties for the artists on the platform. While the rise of these platforms displaced the music piracy happening in the industry, it also decreased amount of revenue that artists were receiving from their recorded music. This thesis shows that platforms have the ability to raise subscription prices while keeping their current user base, thus bringing more revenue into the industry and putting more money in the artists' pockets.

Table A1: Structural Equation Modeling Survey

Construct	Item	Variable	Source
Attribute Satisfaction			
(Algorithm)	I tend to seek out music with [Spotify's] suggested music for me based on my listening habits.	X_1	Sun et al. (2006)
(Playlists)	Using and creating playlists are valuable	X_2	Ajzen and Fishbein (1980)
(Followers)	I tend to consult the users I follow regarding what music I should listen to	X_3	Sun et al. (2006)
	Following people on the streaming platform is valuable	X_4	Ajzen and Fishbein (1980)
(Digital Music Library)	I would be sad if I lost my digital music library to technical issues	X_5	Belk (1985)
(Content)	I seek out exclusive content not available on other streaming services, for example, exclusively released albums and video content	X_6	
(Interface)	My decision to use a platform is strongly linked to the platform's interface.	X_7	Plowman and Goode (2009)
Asset Specificity	If I switch to other music streaming platforms, I have to spend a large amount of time to set up my digital music library	X_8	Chiou & Shen (2005)
	If I switch to other music streaming platforms, I have to spend a large amount of time to understand how to use the platform	X_9	
	If I switch to another music streaming platform, I have to spend a large amount of time to set up and find playlists	X_{10}	
	If I switch to another music streaming platform, I have to spend a large amount of time setting up the service to understand my music taste.	X_{11}	
	If I switch to another music streaming platform, I have to spend a large amount of time following people	X_{12}	
Overall Satisfaction	I am happy about my decision to use Spotify	Y_1	Chiou & Shen (2005)
	Overall, I am very satisfied with Spotify	Y_2	
Loyalty Intention	If I have to do it over again, I would choose Spotify	Y_3	Chiou & Shen (2005)
	I consider myself to be a loyal patron of Spotify	Y_4	
	If Spotify raised their price by a small margin, I would continue to use Spotify	Y_5	

Table A2: Conjoint Analysis Features

FEATURE	LEVEL	RANGE
Personalization (Algorithm)	1	Streaming platform does not use an algorithm to offer suggested music to match your tastes
	2	Streaming platform offers suggested music through an algorithm based on the user's listening habits
Social Aspect	1	Users cannot search or follow other users on the platform
	2	Users are able to search for and follow other users on the platform
Playlists	1	Users do not have the ability to create playlists
	2	Users are able to organize music into playlists
Saved Music Library	1	Streaming is possible only when connected to the Internet
	2	Music download for offline listening is offered and saved in a digital music library in addition to streaming
Price	1	$4.99
	2	$10.00
	3	$14.99
	4	$19.99

Figure A1: Example of a survey choice card

Which of the following music streaming platforms would you choose?

Streaming Platform A	Streaming Platform B	Streaming Platform C	
Downloaded Music	Streaming is possible only when connected to the Internet	Music download for offline listen-ing is offered and saved in a digi-tal music library in addition to streaming	Music download for offline listen-ing is offered and saved in a digi-tal music library in addition to streaming
Social	Users cannot search or follow other users on the platform	Users are able to search for and follow other users on the platform	Users cannot search or follow other users on the platform
Algorithm	Streaming platform does not use an algorithm to offer suggested music to match your tastes	Streaming platform offers sug-gested music through an algo-rithm based on the user's listen-ing habits	Streaming platform offers sug-gested music through an algo-rithm based on the user's listen-ing habits
Playlists	Users do not have the ability to create playlists	Users are able to organize music into playlists	Users are able to organize music into playlists
Price	$14.99	$9.99	$4.99
	CHOOSE	CHOOSE	CHOOSE

Go back

NONE OF THE ABOVE

Figure A2: Original SEM results

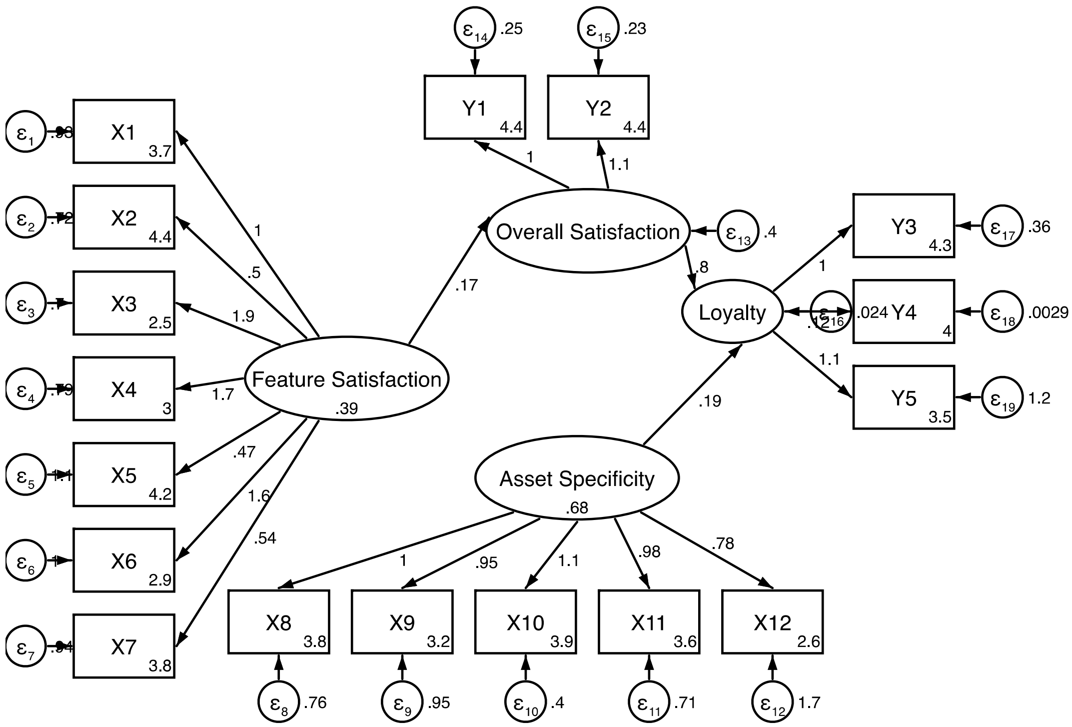
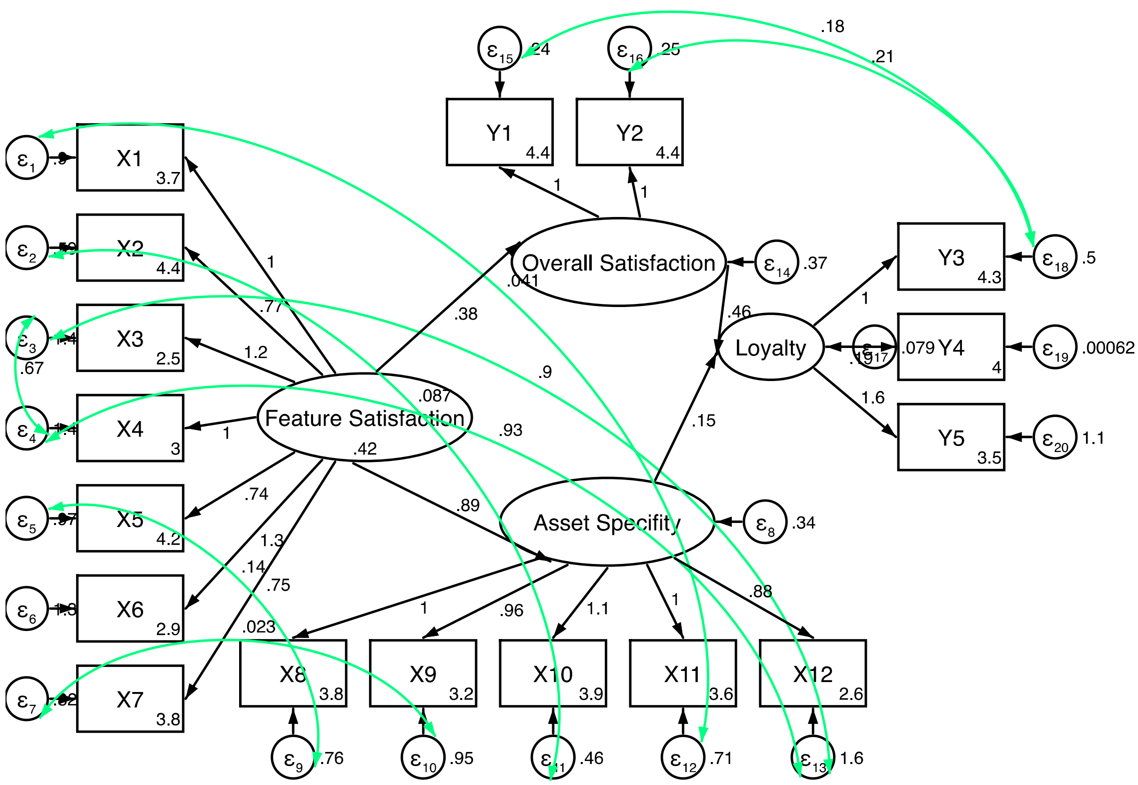


Figure A3: Updated SEM results



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