Contents

List of Figures

List of Tables

Abbreviations

- **MSS** → Music Streaming Services
- **SEM** → Structural Equation Modelling
- **PCA** → Principal Component Analysis
- **EFA** → Exploratory Factor Analysis
- **PE** → Performance Expectancy
- **EE** → Effort Expectancy
- **PV** → Price Value
- **PF** → Premium-Freemium Fit
- **SM** → Shared Subscription Models
- **SL** → Social Listening
- **PG** → Perceived Gains of Music Listening

- **MH** → Music Listening Habits
- **FT** → Features
- **VM** → Wide Musical Taste

ABSTRACT

Music has played a substantial role in enriching human lives from the early stages of civilization and before. While this role has endured, music consumption habits have been constantly evolving through ages. Rapid digitalization of musical records has significantly modified the music consumption habits by giving birth to online Music streaming services. A huge decline in sales of physical copies of music records is a strong indication that Music streaming platforms are already shaping the music listening experience of humans. With already a huge digital market in the Music industry been established, many music giants like Spotify, YouTube, Apple, and Amazon have already made the music industry very competitive.

This study intends to identify the factors that significantly influence consumer's choice & usage of Music streaming service, highlighting each platform's strengths and weaknesses. An extended version of the Unified Theory of Acceptance and Use of Technology (UTAUT2) was applied to identify such significant factors and to compare the relative performance of each streaming platform under each influencing factor. Structural Equation Modelling (SEM) was used to statistically model this framework using the data collected from a survey with 249 responses. My findings confirm that factors such as *Performance Expectancy*, *Effort Expectancy*, *Price-value*, and *Perceived premium-freemium fit* significantly influence consumer's choices of Music streaming services and their intention to purchase a premium version. The results also highlight the strengths and weakness of the platforms studied (*Amazon & Apple music, Spotify, and YouTube*) with Spotify demonstrating more strengths compared to the competitors.

Key Terms: Music Streaming Services, Technology Acceptance Models, Consumer intention, Spotify, YouTube, Apple, Amazon, Premium Subscription

This dissertation follows a structure used by Barata and Coelho (2021).

1. INTRODUCTION

1.1 BACKGROUND

Music has played a significant role in enriching human lives by bringing in peace, joy and emotions from the early stages of civilization and before. Music has also enabled diverse people to bond with each other culturally and emotionally, thus bringing peace, harmony, and unity to society (Larsen et al., 2009). While this role of music in human society has continued through generations, the mode of consuming music has constantly been evolving, significantly impacting music consumption habits. Initially, music could only be enjoyed in live performances. Pre-recorded music is relatively a recent phenomenon, first accessed through the gramophone (Albright,2015), but technological advancements led to inventions like cassette tapes and CDs which, commercializing music through sale of physical copies to consumers (Albright, 2015). But with time, this format of music sales started to suffer the impact of rapid digitalization (Arditi, 2014), invention of Napster in 1999 demonstrated a potential global market that the music industry was yet to explore through digital distributions of music. (The Editors of Encyclopedia Britannica, 2023) This realization led to the emergence of Music streaming services like Spotify in 2006, Tencent Music in 2016, Apple Music in 2001 and Amazon Music in 2007 (Wikipedia contributors, 2023a), (Wikipedia contributors, 2023b), (Wikipedia contributors, 2023c).

The music industry has generated about $26.2Bn revenue in the year 2022, out of which 67% of the revenue was generated through Music streaming services (**MSS**) (IFPI.Org), and the remaining were through sale of physical copies and performance rights. Also, the contribution of MSS to the overall music industry's revenue has been growing constantly for the past 8 years and is projected to grow in the future (Grandviewresearch.com). This is supported by the fact that 48.3% out of 67% of revenue through MSS were from consumers with active subscription plans whose proportion has seen a growth of 10.3% in the year 2022 (IFPI.Org). With such potential market in the future, many music giants are trying to conquer the musical world through their platforms. Currently Spotify accounts for about 32% of global streaming service's revenue generation followed by Apple music at 15.02%, YouTube at 13.66% and Amazon Music at 12.63%. (Curry, 2021) While revenue generated by each platform seems to be a sensible way to compare each other, this scenario might not remain the same in the future. For example, among the mentioned platforms YouTube is the one with significantly higher number of users, totaling to 2Bn, despite contributing lesser proportion in revenue generated (Curry, 2021), while others manage to produce more revenue than YouTube with less than 1Bn users. This inconsistency is because each platform offers significantly different services and subscription packages to attract a very diverse group of music listeners. **Error! Reference source not found.** gives an overview of the services and the subscription models offered by top streaming platforms: (Pendlebury, 2023)

	Spotify	Apple	Amazon	YouTube
Monthly fee & services	£11 - Ad free, Unlimited Music.	£11 - Unlimited music. £17 - Unlimited music, cloud storage, Apple TV	£11 – Ad Free, Unlimited music. £9 - with Prime subscription and limited music	£11 - Unlimited Music, Ad-free music video streaming.
Free option	Yes, with ads.	No	Yes, with ads.	Yes, with ads.
Music library size (songs)	80 million	over 100 million	over 100 million	60 million
Music quality	128kbps - Free, 320kbps - Premium	3730 kbps - Premium	128 kbps - Free 3730 kbps - Premium	256 kbps - both free and Premium
Family plans monthly fees	£17 - 6 members	£17 - 6 members	£16 - 6 members	£17 - 6 members
Student monthly fees	£6	£6	£6	£5
Offline listening	Only with Premium	Only with Premium	Only with Premium	Only with Premium
Podcasts	Yes	Yes	Yes	Yes

Table 1 - Summary of top streaming platform

The price of the premium packages offered by all mentioned streaming services are nearly the same, at £11/Month, but the services offered for the same price are different. Similarly, aspects like Music Quality, Library size and Student plans etc. also vary across providers. To be more specific, from the above table, Spotify is the only streaming service that does not offer any benefits other than ad-free, unlimited music to its premium subscribers, but still manages to hold the highest number of premium subscribers (Armstrong, 2020). This may be attributed to the fact that it satisfies most of the premium user's expectations, like providing personalized song recommendation, strong playlist enhancing algorithms, collaborative listening, or connective features. (Pendlebury, 2023), (Andy, 2021). But these factors cannot be declared as solid reasons behind Spotify's huge premium subscribers as we don't know which of these factors were hugely rated by Spotify subscribers, motivating them to buy a premium subscription. Thus, it becomes necessary to understand consumer's expectations when it comes to music listening to identify the factors influencing consumer's choice and usage of MSS.

1.2 OBJECTIVE

This investigation seeks to identify the factors that consumers consider the most when using a streaming service of their preferred choice. It will comparatively analyze the performance of the above-mentioned streaming platforms under such identified factors, thus recognizing the strengths and weakness of each platform. The reason behind choosing only YouTube, Spotify, Apple & Amazon Music for this study is because, these platforms accounts for majority of MSS's revenue generation and these are the only music platforms that are available in most of the countries making them globally recognizable and representative of Music industry (Curry, 2021), (Santangelo, 2022). Technology acceptance model such as the Unified theory of Acceptance & Use of Technology (UTAUT2) was adapted to form the foundation of this study. Using a questionnaire, this model identifies significant factors influencing consumer's intention to use a piece of technology (Music Streaming service in our case). Respondents to the questionnaire were focused to be in the age range of 15- to 35-year-old people, as studies show that they are comparatively more likely to stream music than others, accounting for majority of these platform's revenue and usage (Susic, 2022), (Ferjan, 2022). The collected responses were statistically analyzed employing Structured Equation Modeling (SEM), leading to the derivation of necessary outcomes and conclusions as explained in the following sections.

1.3 ORGANIZATION

This report is divided into five sections, as follows:

1. This section (the first) gives a brief overview of MSS and their contribution to the Music industry and gives a background of this investigation.
2. The second section provides a literature review on the relevant research and studies that provides the base for this investigation, followed by a series of hypotheses that will be later tested on the collected data.
3. The third section explains the methodology used to conduct this study, from data collection to application of relevant statistical model.
4. The fourth section presents the results of the analysis, which are used to test the proposed hypothesis.
5. The last section summarizes the conclusions behind the results of analysis. Limitations and future scope of this study are also discussed in this section.

2. LITERATURE REVIEW

2.1 TECHNOLOGY ADOPTION MODELS

As mentioned in the previous section, understanding consumer's expectations is vital to grow as a service industry, so this study intends to use a model that explains the factors influencing consumers to use music streaming services (**MSS**), ultimately explaining the drivers behind consumer's choices.

MSS are considered as information systems, the domain under which technology adoption models such as Theory of reasoned action (**TRA)**, Technology acceptance Model (**TAM)** & Unified theory of acceptance & use of technology (**UTAUT)** were applied to understand consumer's views and perceptions (Barata and Coelho, 2021). TRA developed by Fishbein & Ajzen (1975) laid the foundation for technology adoption models which led to derivations of other successful models, TAM was the first derivation from TRA which explained that the trade-off between perceived usefulness and perceived difficulty in using a technology will influence people's intention to use it (Davis, 1989). Extensions of this model, TAM2 & TAM3 were developed in the following years by Venkatesh and Davis (2000), (1996) highlighting the original model's weaknesses like, its reduced focus on technological impact on performance output and blind assumption that technology will improve performance.

These limitations led to the development of a more unified theory of technology acceptance model called UTAUT, which is based on four constructs: 'Performance Expectancy', 'Effort expectancy', 'Social Influence' & 'Facilitating conditions' (Venkatesh et al., 2003). The UTAUT model was developed for use in an organizational context, where the user will not be responsible for the cost associated with it, making it unfit to be used in a non-organizational context. Thus, Venkatesh et al. (2012) developed an extended version named UTAUT2 model to overcome this limitation. This model explained consumer behavior using the existing constructs of UTAUT along with its own extensions 'Price-value', 'Hedonic Motivation' and 'Habit'. The model proved its robustness and versatility by explaining 75% of consumer's behavioral intention under various technological contexts and domains (Venkatesh et al., 2012).

Barata and Coelho (2021) developed an extended version of UTAUT2 by introducing new constructs like 'Perceived premium-freemium fit', 'Involvement & Interest', and 'Personalization' to the existing constructs of UTAUT2 to fit the model in the context of **MSS.** They used this model to understand the factors that influence consumers intention to subscribe to a premium version of MSS, proving that factors 'Facilitating conditions' and 'Personalization' were insignificant in influencing consumer's intention, while the remaining constructs 'Performance Expectancy', 'Effort Expectancy', 'Price-Value', 'Hedonic Motivation', 'Habit', 'Perceived Premium-Freemium fit' were significant (*Fig 1*).

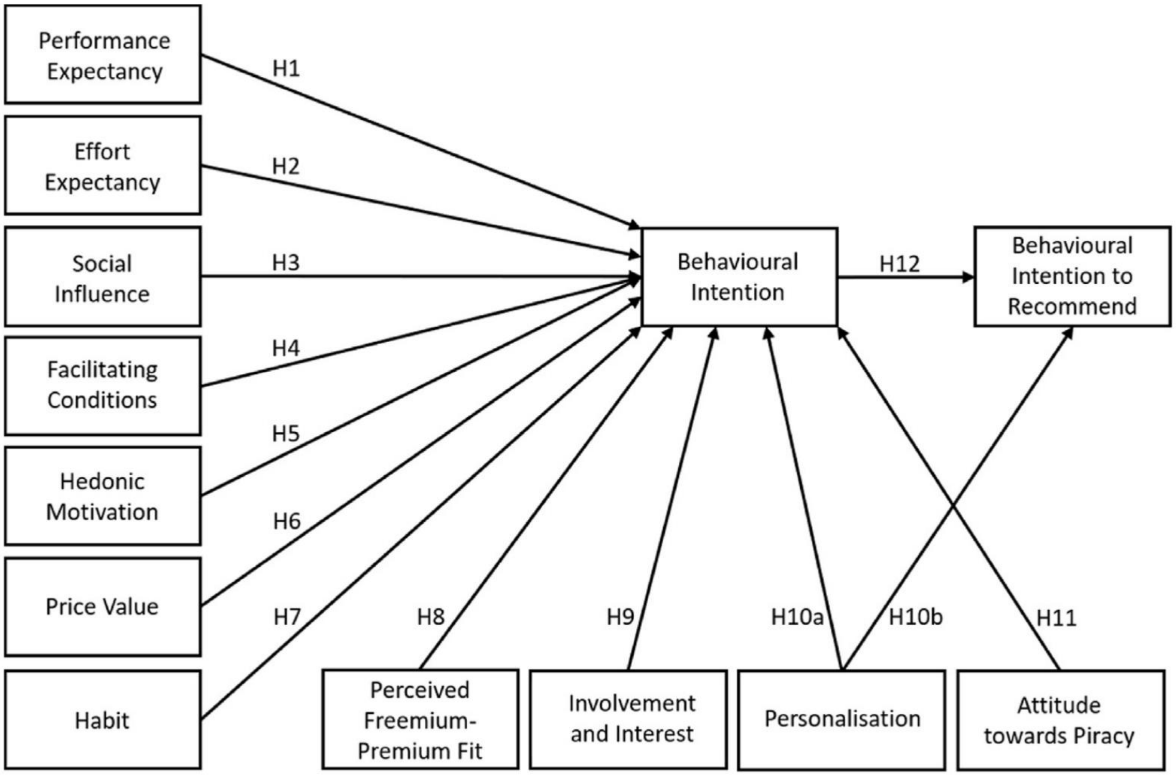


***Fig 1**: Extended version of UTAUT2 Model proposed by Barata and Coelho (2021).*

This study intends to use an extended version of Barata and Coelho (2021)'s model by adopting the constructs that were proven to have significant impact on consumer's intention, along with custom and novel constructs, to identify the factors that influences consumer's choice & usage of MSS, highlighting the strength and weaknesses of major MSS platforms. The constructs of the research model and its respective hypothesis are discussed in the below sections.

2.2 RESEARCH MODEL & HYPOTHESES

The proposed research model consists of 10 constructs out of which the first 5 are incorporated from the model developed by Barata and Coelho (2021). The incorporated constructs 'Performance Expectancy', 'Effort Expectancy', Price-Value', 'Perceived Premium-Freemium fit' and 'shared-subscription model' were proved to have significant impact on consumer's intention to adopt and use a MSS. (Barata and Coelho, 2021). These 5 constructs are mainly focused on the performance parameters and the outputs of MSS which influences consumer's intention on streaming platforms. The remaining 5 extended constructs 'Social Listening', Perceived gains of music Listening', 'Music Listening habits', 'Features' and 'Wide taste in Music' were derived to understand if consumer's musical choices or preferences influence their choice & usage of MSS. The theoretical background behind the extended and the incorporated constructs are discussed below with their respective hypothesis.

The diagram of the proposed model is as follows:

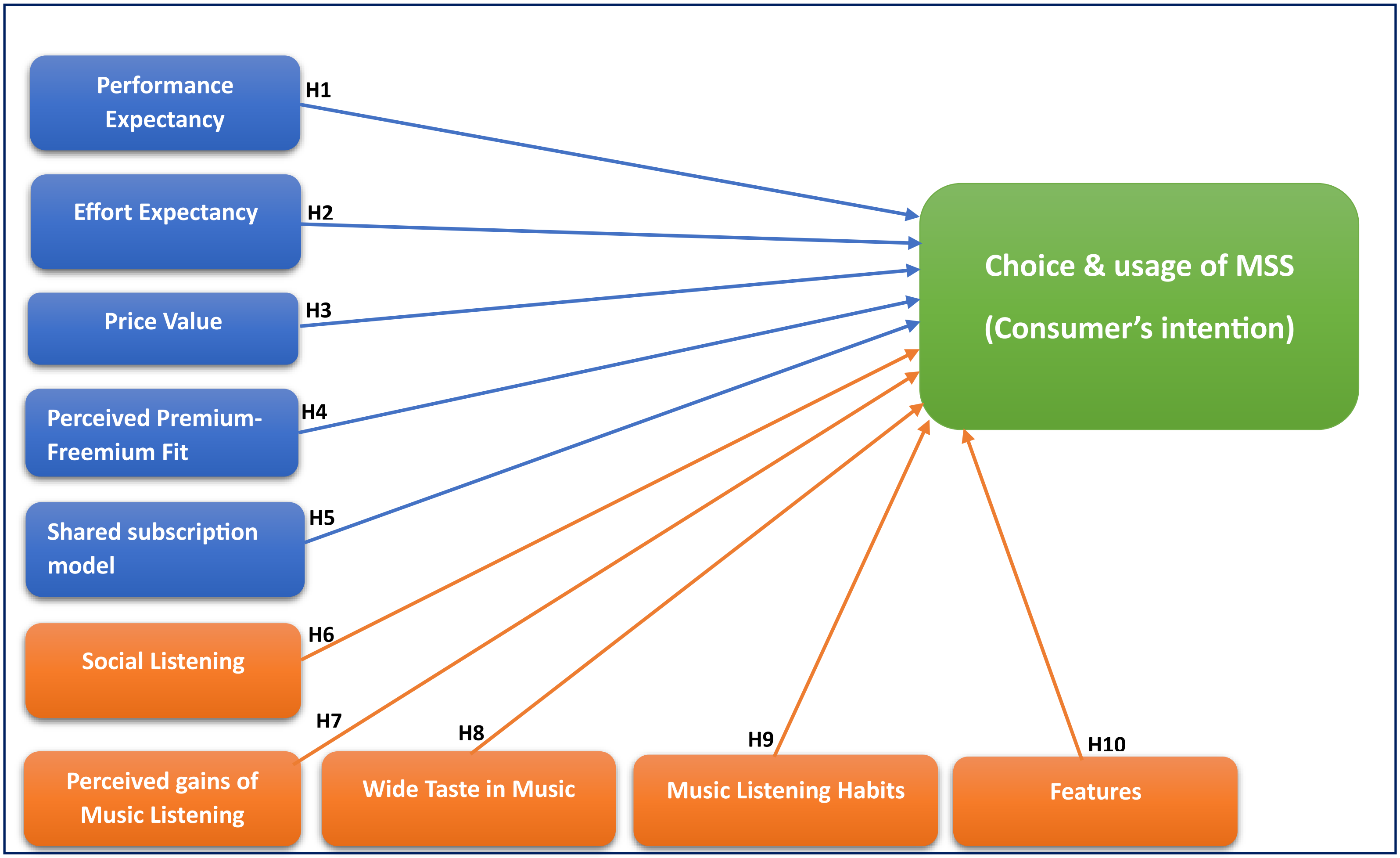


***Fig 2**: Proposed Research Model with extended constructs*

2.2.1 Incorporated Variables

A. Performance Expectancy

Performance Expectancy is defined as the degree to which an individual believes that using a piece of technology will bring benefits to his/her functional aspects of performing a certain activity (Venkatesh et al., 2012). Perceived usefulness and outcome expectations form the root constructs (Base theoretical concept explaining user's behavioral intention) for performance expectancy (Akinnuwesi et al., 2022). Combining these roots (Chu and Lu, 2007) proposed that the degree to which Music streaming services (MSS) fulfill certain aspects that the consumer believes will improve their music listening experience is the performance expectancy of MSS. Thus, this construct focuses on attributes that bring in necessary utility and tools that consumers expect from a MSS to make their music listening more entertaining, thus improving the experience (Hampton-Sosa, 2019). Such attributes are recommendation algorithm suggesting songs and playlist suiting consumer's musical taste, enjoyment from discovery of new music and sufficient access to Artist & album information (Hampton-Sosa, 2017). Thus, this construct focuses on shaping questions to understand consumer's expectations on such utility and functions that MSS brings. The hypothesis is formulated as:

H1: ***Performance Expectancy is positively related to the consumer's usage level of their preferred choice of MSS.***

B. Effort Expectancy

Effort expectancy is defined as the degree of ease associated with using a piece of technology (Venkatesh et al., 2012). Davis (1989) claimed that the more a piece of technology is deemed to be easy to use, more the probability that the consumer will adopt and use it. Kwong and Park (2008) stated that more effortless it is to use a Music streaming service (MSS), consumers will find the music listening experience to be more entertaining, and the platform to be useful satisfying the root constructs 'perceived usefulness' and 'ease of use' associated with consumer's intention to adopt a piece of tech (Davis, 1989). This construct focuses on attributes that are associated with making the music listening experience more effortless through the usage of MSS. Such attributes are ease of locating music libraries, aesthetic design of the streaming platforms, exploring, creating, and sorting playlists or songs effortlessly (Hampton-Sosa, 2017). Thus, this construct's questions are focused on understanding consumer's expectations on attributes responsible for making a streaming platform effortless to use. The hypothesis is formulated as follows:

H2: ***Effort expectancy is positively related to the consumer's usage level of their preferred choice of MSS.***

C. Prive Value

"Price value is defined as the cognitive trade-off between the perceived benefits of an application and the monetary cost associated with it" (Venkatesh et al., 2012). This construct is claimed to be one of the most significant factors influencing consumer's intention in using a piece of technology (Dodds, 1991), (Venkatesh et al., 2012). In the context of MSS many platforms offer both free versions and premium versions, but premium subscribers generate more profits (Barata and Coelho, 2021). So, this construct mainly focuses on understanding if consumers perceive that the benefits of using a premium version of a streaming platform is greater than the monetary value associated with it by asking questions related to the premium packages offered by their preferred choice of MSS. The hypothesis is formulated as follows:

H3: ***Price-Value is positively related to the consumer's intention to opt for a premium version of their preferred choice of MSS***.

D. Perceived Premium-Freemium Fit

MSS offer both premium as well as freemium versions of their services, making it necessary to evaluate the adjustment between both versions. Perceived premium-freemium fit is defined as the degree of similarity between the free and paid versions of an online music streaming platform (Barata and Coelho, 2021). If this fit is high, it indicates that the free version offers the required premium features that the customers expect, making it unnecessary to upgrade to a premium version, but premium subscribers generate more profit. So, there should be significant difference in the MSS's usage experience between the free and paid versions to make customers upgrade to a premium version (Hamari et al., 2020), (Wagner et al., 2014). MSS brings in some restrictions in their free versions like limited number of music listening hours, streaming advertisements in between and restricting offline access to make their premium versions more attractive (Wagner et al., 2014). (Li and Cheng, 2014) claimed that people who were able to tolerate Ad and other restrictions opted for a free version rather than a paid one. So, this construct's questions are focused on understanding how people perceive these restrictions which influences their intention to adopt a premium version. The hypothesis is formulated as:

H4: Perceived premium-freemium fit is negatively related to consumer's intention to opt for a premium version of their preferred choice of MSS.

E. Shared-Subscription Model

(Hampton-Sosa, 2019) claims that product sharing is positively related to consumer's intention to adopt digital technologies such as MSS. As discussed earlier, price-value influences the customer's intention to adopt a premium version of MSS. So, many platforms offer shared-subscription models to consumers giving them a variety of options to opt for a premium version (Pendlebury, 2023). Iyengar et al (2020) claimed that attractive shared-subscription models will improve the probability of a consumer upgrading to a premium version. Thus, this construct focuses on understanding how consumers perceive the shared-subscription models offered by their preferred choice of MSS. The hypothesis is formulated as:

H5: Shared-subscription model is positively related to consumer's intention to opt for a premium version of their preferred choice of MSS.

2.2.2 Additional custom Variables

F. Social Listening

Perceived enjoyment in using a piece of technology is considered as a significant factor influencing consumer's willingness to adopt it (van der Heijden, 2004). (Hampton-Sosa, 2019) stated that product sharing is an important aspect in bringing enjoyment to people by creating a sense of belonging to the consumers. It helps consumers to discover new products or ideas or to bond with like-minded people. In the context of MSS, the ease with which people can share their music libraries or the ability to listen music collaboratively with the people they wish influences their choice of MSS (Hampton-Sosa, 2017). Thus, this construct focuses on understanding the relationship between consumer's expectations of collaborative music listening to the usage level of their preferred choice of MSS. The hypothesis is formulated as:

H6: Social Listening is positively related to the consumer's usage level of their preferred choice of MSS.

G. Perceived gains of Music Listening

Music streaming services (MSS) can be considered as technology delivering pleasure by creating entertainment using music (Chen et al., 2022). Perceived enjoyment is an important factor influencing technology adoption (van der Heijden, 2004). Ueda et al (2013) claims that Music listening can impact the attitude, well-being and motivation levels of a person based on how they perceive music listening. Styvén (2010) stated that a person strongly believing in gains or more involved a person is into music listening, he/she is more likely to adopt any technology related to music. Thus, this construct tries to understand the relationship between consumers' perceived enjoyment and gains of music listening to the usage level of their preferred choice of MSS. The hypothesis is formulated as:

H7: Perceived gains of music listening by consumers is positively related to the usage levels of their preferred choice of MSS.

H. Music Listening Habits

Habit is a construct that has significant influence in consumer's behavioral intention (Kim and Malhotra, 2005). Stratton and Zalanowski (2003) state that people under the age range of 15-30 have habits of listening to music daily and during daily activities like commuting, studying, sleeping and physical workouts. More the people listened to music during their daily activities the more their involvement with music (Stratton and Zalanowski, 2003). The more involved a person is in music listening, the more will be their intention to adopt any digital technology related to music listening that suits their music listening habits (Styvén, 2010). Thus, this construct aims to identify if there is a relationship between consumer's music listening habits and their usage level of their preferred choice of MSS. The hypothesis is formulated as:

H8: Music listening habits of consumers is positively related to the usage levels of their preferred choice of MSS.

I. Features

Perceived quality of digital technology has direct influence on consumer's intention on adopting and using it, perceived quality can be defined in many ways depending on the context (Hampton-Sosa, 2017). Performance features such as Audio quality, hardware integration of applications, accessibility and product portfolio play a significant role in influencing the perceived quality of MSS (Kuei and Madu, 2003), (Hampton-Sosa, 2017). Thus, this study focuses on understanding if there is a relationship between such performance features and customer's usage level of their preferred choice of MSS. The hypothesis is formulated as:

H9: Features offered by MSS are positively related to the usage levels of their preferred choice of MSS.

J. Wide taste in Music

The more interested and involved a consumer is in a service or product the greater will be his/her evaluation of the choices or alternatives available (Bian and Moutinho, 2009). Each Music streaming service's library size and music collections are different from each other (Pendlebury, 2023), (Hampton-Sosa, 2017). Cesareo and Pastore (2014) proved that exposure to variety of music and deep interest in music to be significant factors influencing consumer's intention towards adopting and using a MSS. Thus, this construct tries to understand if consumer's wide variety of taste and deep involvement in music can influence the usage level of their preferred choice of MSS. The hypothesis is formulated as:

H10: Involvement in listening to a wide variety of music is positively related to the usage levels of their preferred choice of MSS.

2.3 Previous studies and Research Gaps

Many studies have been done about MSS adoption earlier using Technology acceptance models such TRA, TAM and UTAUT2. Several of these studies proved that Perceived usefulness, Ease of use, Perceived quality, and Perceived enjoyment to be critical factors influencing consumer's intention to adopt and use a MSS (Hampton-Sosa 2017, Guerra and Fernandes 2019, Hampton-Sosa 2019 and Kwong and Park 2008). Study done by Helkkula (2016), used UTAUT2 model, to prove that factors such as Hedonic motivation, price value, habits and involvement & interests also influence consumer's intention towards MSS. Dörr et al (2013) proved that attitude towards digital piracy also influenced consumer's intention. Barata and Coelho (2021) used all the previous studies as a base to identify factors that influenced customer's intention to purchase a premium version of a MSS.

All these previous studies were focused on identifying the factors that had significant impact on consumer's intention to adopt an MSS, but these studies did not try to understand consumer's expectations which influences their choice & usage of a MSS from the existing options. This study realizes this research gap and uses the factors or constructs that were already proven to significantly influence consumer's intention on MSS to understand the expectations of consumers using various MSS and use these results to comparatively analyze the performance of each streaming platforms under such significant factors to identify each platform's strength and weaknesses.

3. METHODOLOGY

3.1 DATA COLLECTION

Based on the proposed UTAUT2 model, a questionnaire was drafted to test the hypotheses derived in each construct of the model. The questionnaire was divided into thirteen sections, the first section asks the respondent to report their usage level of music streaming platforms: *Free & premium versions of YouTube & Spotify, Amazon music, Apple music, and others*, using a 5-point Likert scale (*Very Frequently to Never or Almost never*). This is to understand each consumer's usage levels of their preferred choice of MSS. The next ten sections include questions indicating the respondent's level of agreement with the hypothesis of the following constructs: *Performance expectancy (**PE**), Effort expectancy (**EE**), Price-Value (**PV**), Perceived Premium-Freemium fit (**PF**), Shared-Subscription models (**SM**), Social Listening (**SL**), Perceived gains of Music Listening (**PG**), Wide Musical taste (**VM**), Music Listening Habits (**MH**), and Features (**FT**)*. These questions used a 7-point Likert scale (*Strongly Disagree to Strongly Agree*) to measure respondent's agreement with each statement. The statements used in the first 11 sections of the survey are presented in (*Table 2*).

The following section is an optional question asking the respondent to type in any concerns or recommendations that they feel could improve their music listening experience. This section will be qualitatively analyzed and discussed in the Results section. The last section focuses on demographic info like age & gender, employment status and household income. Questions in the last two sections were made optional for the respondent, as they are not a core part of the research model. Only the first eleven sections are part of the research model, where the first section acts as Dependent variable while the remaining 10 sections will act as independent latent variables in the research model.

The survey was distributed using Qualtrics application (Qualtrics, 2015) and was mostly focused on people from the age range of 15-35, as they contribute to a major proportion MSS usage (Susic, 2022). So, the survey was mostly distributed to university students and graduate employees to make sure that the respondents fell within the mentioned age range.

Construct (latent)	Code	Questions/Indicators
Performance Expectancy (**PE**)	**PE1**	My Preferred choice of MSS: have enhanced my playlists by recommending the right set of music suiting my musical taste.
	PE2	recommends the perfect playlists or songs suitable for various occasions or moods, for example Workout playlist, travelling playlist or Romantic Playlists etc.
	PE3	have introduced me to a diverse range of music genres I didn't knew I would like listening to, expanding my musical horizons.
	PE4	provides me with enough information about the artists or bands that I follow.
	PE5	have significantly improved the overall music listening experience.
Effort Expectancy (**EE**)	**EE1**	My Preferred choice of MSS: makes music listening sessions effortless.
	EE2	makes it effortless to create and maintain the playlists.
	EE3	User-interface makes it effortless to navigate through its features and music collections.
Price-Value (**PV**)	**PV1**	My Preferred choice of MSS: offers a variety of attractive premium packages.
	PV2	premium subscription provides good value for money.
	PV3	premium version is affordable and cheap.
Perceived Premium-Freemium fit (**PF**)	**PF1**	I prefer listening to ads and face other restrictions than paying for a music streaming service.
	PF2	Listening to advertisement is a small price to pay for a free service.
	PF3	The free and premium services of my preferred music streaming service are very similar.
Shared-Subscription Model (**SM**)	**SM1**	I would like to subscribe or continue using a shared subscription model with my friends or family members in the future.
	SM2	Shared subscription plans offer as much freedom and usability as individual plans, for less money.
Social Listening (**SL**)	**SL1**	I like sharing my playlist with my friends or family.
	SL2	I like creating playlists in collaboration with my friends or family.
Perceived gains of Music listening (**PG**)	**PG1**	Listening to music gives me great pleasure and joy.
	PG2	Listening to music is motivating and increases my productivity and performance.
	PG3	Listening to music helps me maintain good mental health.
Wide Musical taste (**VM**)	**VM1**	I like listening to remixes, mashups, and cover songs made by non-established artists.
	VM2	I listen to music from a wide variety of languages or cultural backgrounds.
	VM3	I like to have the option of watching videos of the songs that I listen to.
Features (**FT**)	**FT1**	Music with high audio quality is very important to me.
	FT2	Availability of quality podcasts is very important to me.
	FT3	A music streaming service's application should integrate seamlessly with all my devices. For example, controlling the music playing in my laptop from my phone or vice-versa.
Music Listening habits (**MH**)		I listen to music:
	MH1	everyday in a week.
	MH2	during any physical activities like workouts, running or cooking, cleaning etc.
	MH3	during my daily commute or while traveling on vacations.
	MH4	while studying or working.
	MH5	before going to sleep.
Consumer's preferred MSS choice and respective ratings	**SF**	Spotify Free
	YTF	YouTube Free
	SP	Spotify premium
	YTP	YouTube Premium
	AP	Apple Music
	AM	Amazon Music
	OT	Others

Table 2: Overview of Survey Questionnaire.

3.2 PRINCIPAL COMPONENT ANALYSIS (PCA)

3.2.1 Overview of PCA

PCA is an exploratory technique that converts highly correlated variables into a single variance (component) separating them from other uncorrelated variables. It is a linear combination of variables which explains most of the variance in the first component while subsequent components explain the next most of the variance which are highly uncorrelated with the first component. This process continues until complete variance of the given data is explained (Kaiser, 1960). The number of components required to completely represent a variance is determined using the Eigen value of each component. According to Kaiser (1960) Eigen value more than 1 signifies that the given component explains significant amount of variance from the given data, or a scree plot is drawn using these Eigen value to identify the elbow point where the Eigen value drops significantly. Using the mentioned procedure, we can convert a dataset with highly collinear variables into a dataset with only a few variables that are non-collinear, while losing little information.

A limitation of PCA is that, by default, it tries to represent most of the variables in a single variance or component ignoring the high degree of correlations, hence failing to identify the underlying latent factors (Brown, 2014). Factor Rotation is used to overcome this limitation. There are two types of rotation: Orthogonal and Oblique. Orthogonal rotation keeps the factors uncorrelated with each other while in Oblique rotation factors can correlate with each other. The usage of any rotation depends upon the objective of PCA, and this study will use Oblique rotation to identify correlation between indicators (questions) under each section and to simultaneously form highly uncorrelated components for each section of the survey. There are many applications of PCA such as (Brown, 2014)

- **Exploratory Factor Analysis (EFA)** → *To explore the underlying dimensions of collected data*.
- **Confirmatory Factor Analysis (CFA)** -→ *To confirm the hypothesized relationships of collected data.*

3.2.2 Application of PCA

PCA was performed using Promax rotation (Oblique rotation) to confirm that the indicators (questions) within each construct (Sections of survey) are highly correlated with each other explaining the variance of each construct under one single component, while indicators of different sections are highly uncorrelated with each other. So, it was expected that 10 separate components will be formed: one for each construct (PE, EE, PV, PF, SM, SL, PG, VM, FT & MH).

EFA was performed to explore how consumer's choice of MSS is correlated explaining consumer's preferences. User profiles were created based on these results.

Both the EFA and PCA analysis were done in R using 'psych', 'prcomp' and 'gparotation' library. In both the analysis, the loadings of each indicator or variable in all declared components were measured to assign the variables to a single component. This research expects the factor loading to be at least equal to or greater than 0.5 to reliably assign any variable to a component. With the results of both EFA and PCA a statistical model using Structural Equation Modelling (SEM) was built.

3.3 DATA EVALUATION

The reliability and internal consistency of the formed exogenous latent variables were evaluated. The reliability of each construct was measured using Composite reliability and Cronbach's alpha test whose value is expected to be greater than 0.7 which will imply that the indicators under the same construct are corelated to each other and highly uncorrelated with indicators from other constructs ensuring that each latent is reliable and internally consistent (Henseler et al., 2009), (Hair et al., 2013). Average Variance Extracted (AVE) was also calculated to verify the convergent validity of each construct. The AVE is expected to be at least greater than or equal to 0.5 confirming that the latent variable can explain at least half of its indicator's variances (Fornell and Larcker, 1981).

3.4 STRUCTURAL EQUATION MODELLING (SEM)

SEM is a statistical technique used to analyze complex relationships between multiple independent and dependent variables simultaneously (Hair et al., 2021). It works by combining concepts such as Factor Analysis, Regression modelling and Path analysis.

3.4.1 Components of SEM (Hair et al., 2021)

- **Observed Variables (Indicators)** → *These are values that are either directly measured or collected during data collection.*
- **Latent Variables** → *These are constructs which are formed by extracting factors from the observed variables by factor analysis representing the variances of related indicators in a single component (Latent). They are not observed, but instead derived based on the value of indicators.*
- **Residual Variance** → *It explains the variances of the observed variables that did not fit in the proposed latent variable.*
- **Regression Path** → *It is the hypothesized relationship between the variables, it may be either a direct or indirect relationship and might be between a latent or observed variables.*
- **Path Diagram** → *A graphical representation of the statistical model which demonstrates the hypothesized relationship and regression paths between the observed and the latent variables.*

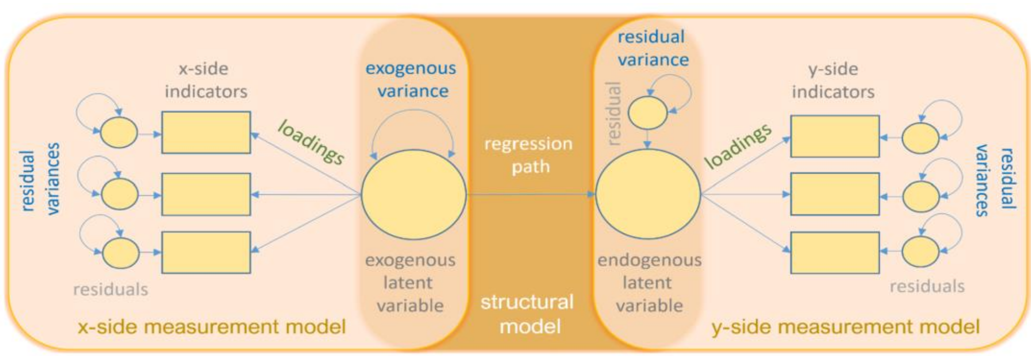


Fig 3: Structure of SEM model with its components. (UCLA.edu)

3.4.2 Methods of SEM (Hair et al., 2021)

- **Covariance-Based (CB) SEM →** This method is used to confirm or reject a proposed hypothesis by determining how closely the theoretical model can reproduce the covariance matrix of an observed dataset. This is also called the Maximum-Likelihood estimation. This method is exclusively used to determine the relationship between hypothesized variables. This method cannot be used to build predictive models as this does not focus on explaining the variance of the dependent variable.
- **Partial Least Squares (PLS) SEM →** This method is used to overcome the limitation of the CB-SEM, by focusing mainly on explaining the variance of the dependent variable using the independent variables, by running multiple iterations resulting in a high-fitting model which generates reliable predictions. Its robustness against non-normal data and its ability to produce high-fitting models are its core strengths.

3.4.3 Evaluation of SEM Model

The developed SEM model can be evaluated using the below measurements.

- **Comparative Fit Index (CFI) →** CFI is a measure of how well the proposed model fits with the observed data, this index is determined by comparing the proposed model to a baseline model (an assumed model where all the variables are uncorrelated) (UCLA.edu).

- **Tucker Lewis Index (TLI) →** TLI is another fit that works very similar o CLI except it also considers degree of freedom associated in the proposed model making it more sensitive to complex models. (UCLA.edu)

Both CFI and TLI are expected to be closer to 1 to ensure that the proposed model is closer to a saturated model (*A model that produces the highest fit for the observed data****).***

- **Root Mean Square Error of Approximation (RMSEA) →** RMSEA is the most important parameter to evaluate the fit of the proposed model, it is an absolute measure of determining how well the proposed model fits with the observed data. Unlike CFI and TLI, which generates a comparative evaluation using a saturated model, this gives an absolute measure of the fit. ***RMSEA value less than 0.05 is declared a close-fit and the proposed research model is expected to satisfy this condition***. (UCLA.edu)

3.4.4 Application of SEM

An SEM model was built using 208 records of survey answers. 'Lavaan' package in R-programming Language was used to build the SEM model (Rosseel, n.d.). This research used Covariance-based CB-SEM rather than PLS-SEM as this study intends to find only the relationship between the variables and does not intend to build a predictive model for which PLS-SEM is exclusively used.

Depending upon the results of PCA analysis on the first 11 sections of the research model, 5 endogenous and 8 exogenous latent variables were formed. The path diagram of the developed model is shown in (*fig 4).*

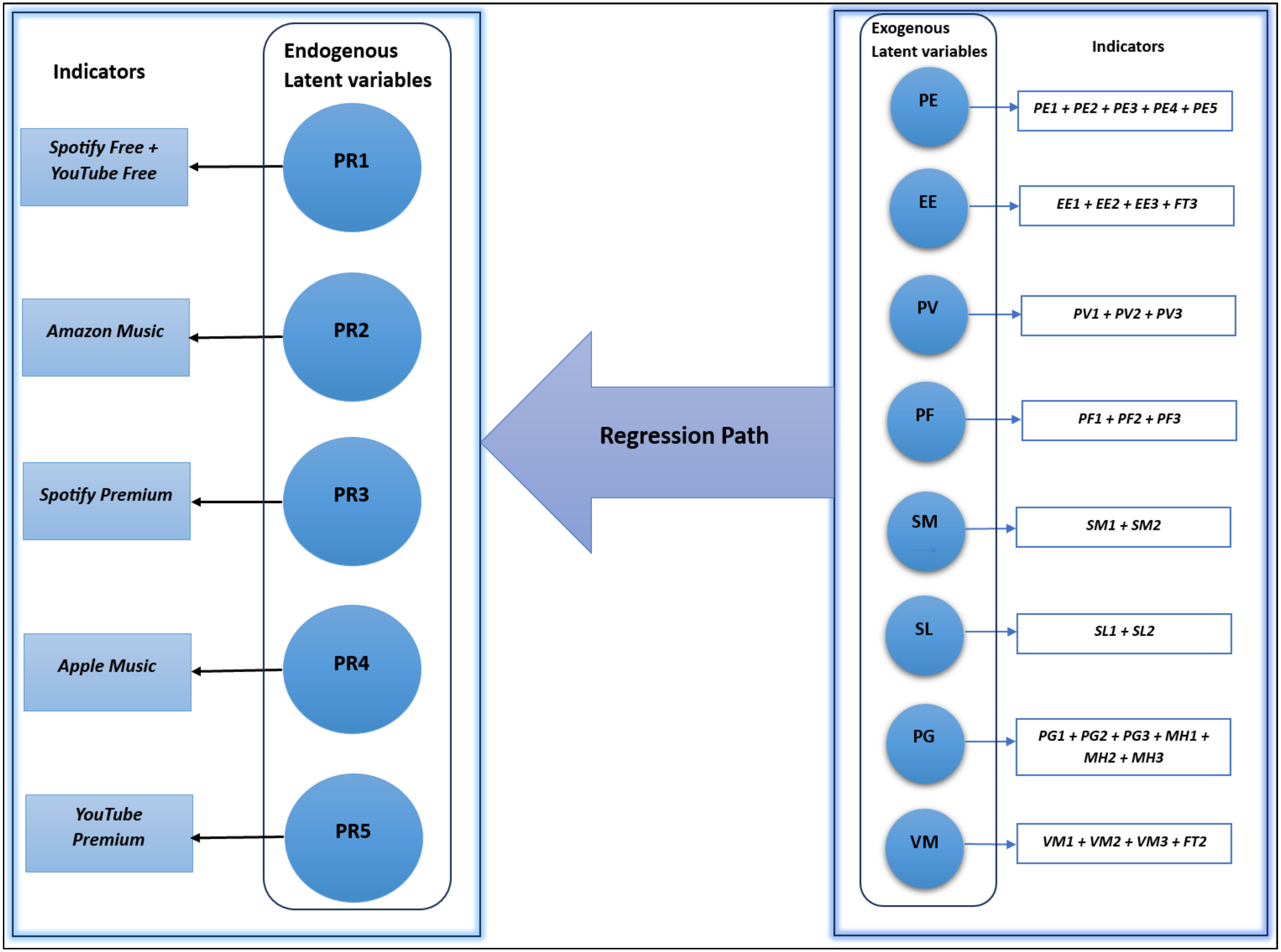


Fig 4: Path diagram of developed SEM model

3.4.4.1 Endogenous Latent Variables

According to the results of PCA analysis of the first section of the research model, both the free versions of Spotify and YouTube loaded together in the same component indicating that the consumers use them together. The remaining platforms Apple music, Amazon Music and the premium versions of YouTube and Spotify loaded separately in individual component indicating that all these platforms were used separately and not together by the consumers. Thus 5 endogenous latent variables (PR1, PR2, PR3, PR4 & PR5) were formed as shown in the path diagram by factor analysis of each individual platform's reported usage levels, thus creating user profiles based on consumer's usage pattern.

3.4.4.2 Exogenous Latent Variables

According to the results of PCA analysis of indicators (questions) from the remaining 10 sections (constructs) of the research model, the indicators loaded together in 8 individual components representing the variance of the 10 constructs. From the path diagram, it can be observed that constructs PE, PV, PF, SI, & SL formed individual components with their respective indicators, while indicators from constructs FT & MH did not, FT3 and FT2 indicators loaded with indicators of EE (EE1 + EE2 + EE3 + FT3) and VM (VM1 + VM2 + VM3 + FT2) respectively, while MH1, MH2, MH3 loaded with indicators of PG (PG1 + PG2 + PG3 + MH1 + MH2 + MH3). Thus, in total 8 exogenous latent variables were formed by factor analysis of the mentioned indicators as shown in the path diagram to regress with the 5 endogenous latent variables formed.

3.4.4.3 Regression Path

5 endogenous and 8 exogenous latent variables were regressed with each other through 5 separate regression equations i.e., a regression for each endogenous latent. The SEM model's regression equations are as follows:

- ***PR1*** *~ PE + EE + PV + PF + SM + SL + PG + VM*
- ***PR2*** *~ PE + EE + PV + PF + SM + SL + PG + VM*
- ***PR3*** *~ PE + EE + PV + PF + SM + SL + PG + VM*
- ***PR4*** *~ PE + EE + PV + PF + SM + SL + PG + VM*
- ***PR5*** *~ PE + EE + PV + PF + SM + SL + PG + VM*

The results of the regressions were used to identify the factors (latent) that significantly influence consumer's usage levels of preferred choice of MSS and the co-efficient value of such significant factors from each regression equation were used to identify each platform's strengths and weaknesses by comparing the relative coefficients. The results of the regressions are discussed in the results & analysis section.

3.4.4.4 Improving and evaluating the fit of SEM model.

Modification-index function which is a part of Lavaan package was used to identify significant co-variances between the indicators and such co-variances were used in the model to improve the fit. The co-variances included in the model are as follows:

- *PG2 ~~ PG3*
- *PE1 ~~ PE2*
- *PF1 ~~ PF3*
- *PG3 ~~ MH3*
- *PG2 ~~ MH3*

The developed model's reliability and fit were evaluated using the parameters RMSEA, CFI and TLI as discussed earlier.

The results of the SEM model were critically evaluated to test the proposed hypotheses and to serve the objective of this research.

4. RESULTS & ANALYSIS

This study collected 249 responses in total using the Qualtrics (Qualtrics, 2015) application out of which 41 responses were deleted as they were either incomplete or answered in a very short timeframe (This study considered responses which took atleast two minutes) or selected the same choices throughout the survey. The remaining 208 complete responses were used for modelling and analysis. The '*Others'* option in the first section where consumers rate the usage level of their preferred choice of MSS was removed from the analysis due to inadequate inputs.

The optional section asking the respondents to type in their recommendations on improving the music listening experience was not analyzed due to very low number of valid inputs from the respondents.

4.1 Demographic info & Stats

Demographic information such as age, gender, Employment status and household income of the respondents were collected to provide a background of the people on whom this study was done. *Table 3* gives the overview of the stats:

Demographic Info	Category	Quantity	Percentage (%)
Age	***Under 18***	2	1.15
	18-24	100	57.47
	25-34	66	37.93
	35-44	2	1.15
	45-54	3	1.73
	55 or Older	1	0.57
Gender	***Male***	96	55.17
	Female	76	43.68
	Prefer not to say	2	1.15
Household Income	***£20,000 or Less***	62	65.26
	£20,001 - £40,000	25	26.32
	£40,001 - £60,000	3	3.16
	£60,001 - £80,000	4	4.21
	£80,001 or more	1	1.05
Employment Status	***Student Not employed***	80	45.98
	Student & employed	27	15.51
	Employed Part time	12	6.9
	Employed Full Time	52	29.89
	Unemployed or Retired	3	1.72

Table3: Demographic info & stats

Age Distribution

As discussed earlier, this study focused on getting responses from people within the age range of 15-35 as they account for majority usage of MSS (Susic, 2022), (Ferjan, 2022), and we can observe from the barch chart that 95.4% of total respondents fall within the age range of 18-34 with over 57.47% of respondents belonging to much younger age range of 18-24 serving this study's objective.

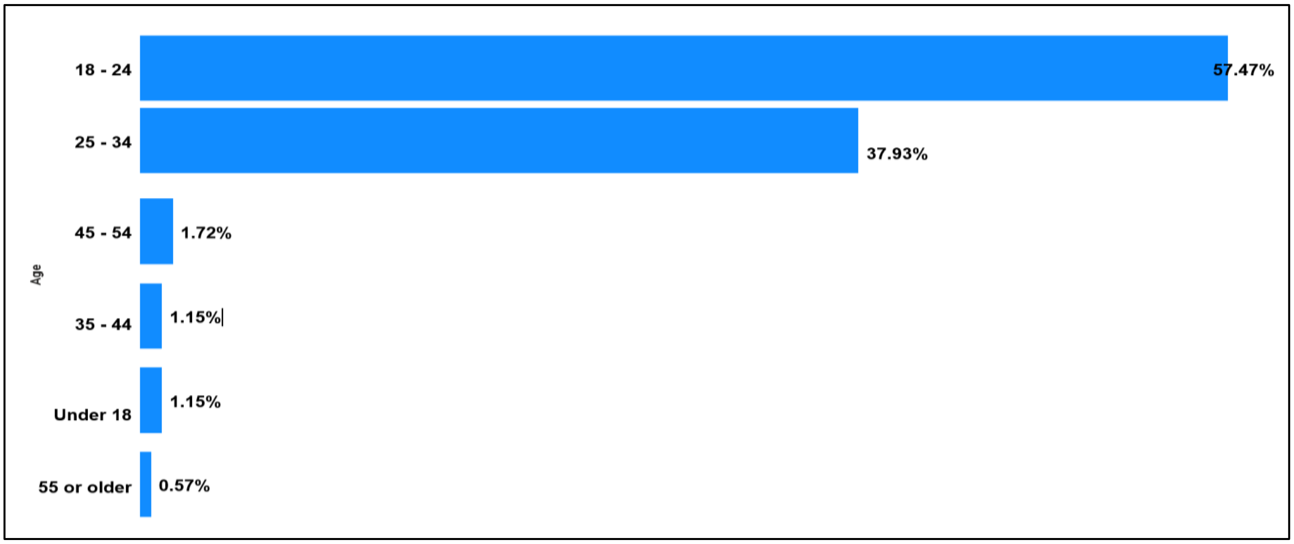


Fig 5: Age distribution

Gender distribution

The proportion of male and female were 55.17% and 43.68% respectively while 1.15% of people preferred not to reveal their gender as shown in the pie chart.

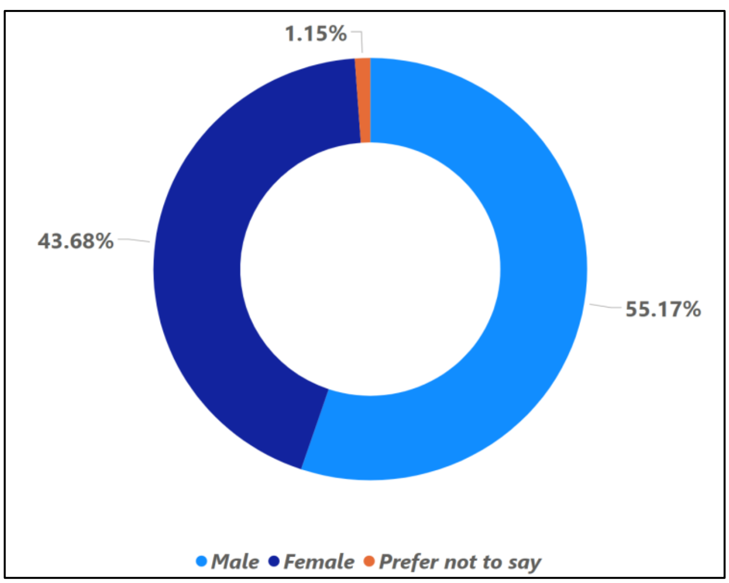


Fig 6: Gender distribution

Household Income

91.58% of respondent's household income were in the range of £20,000 - £40,000 or less than £20,000 per Anum, while nearly just 7% of respondents earned more than £40,000 out of which 1.05% of people earned a very high income of more than £80,000 per Anum.

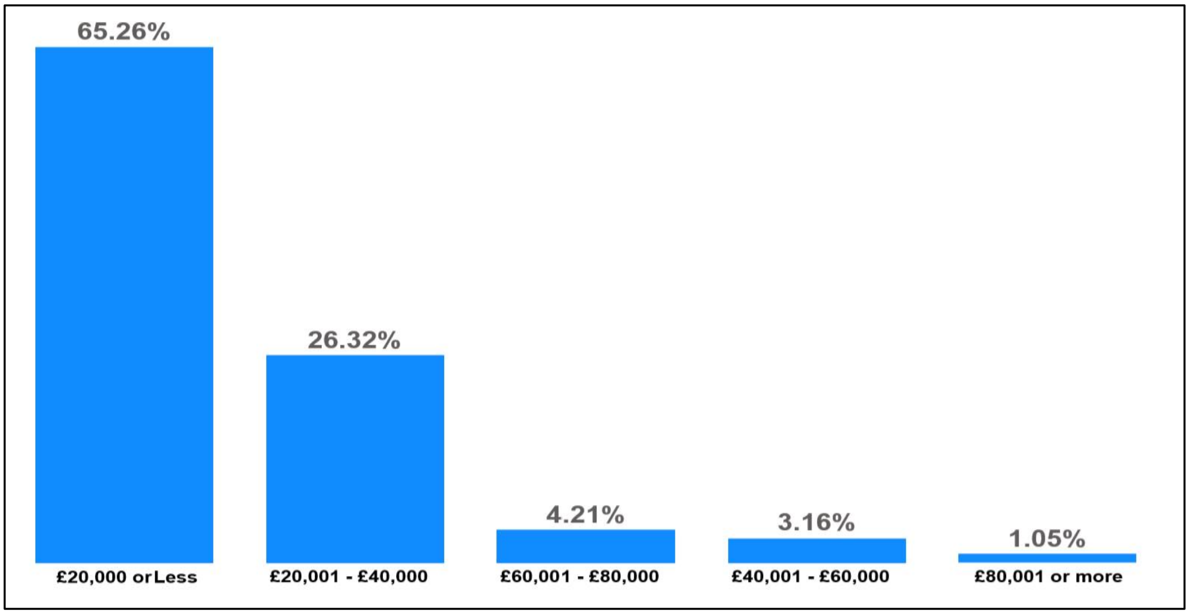


Fig 7: Household Income distribution

Employment Status

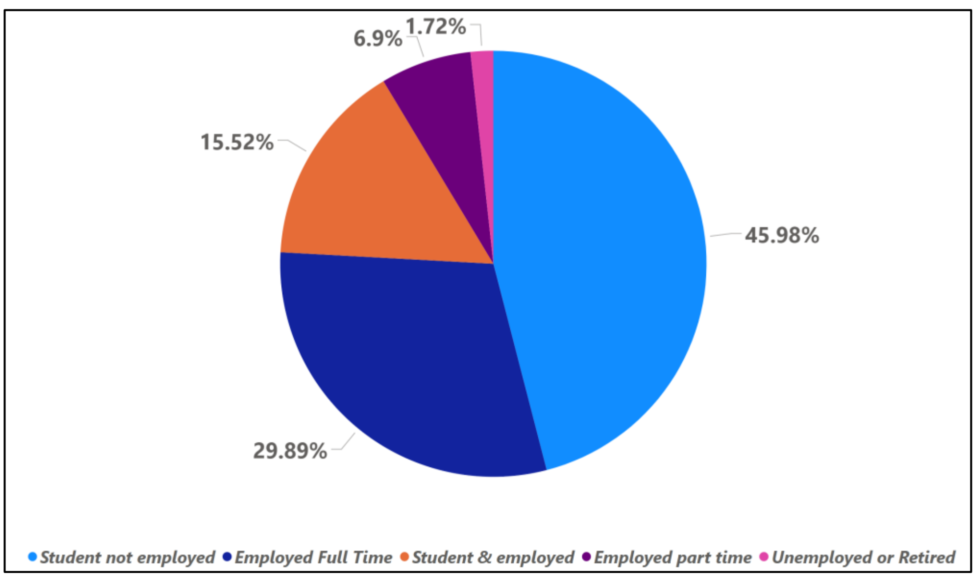


Fig 8: Employment Status

Nearly 46% of respondents were students without any current employment, while nearly 30% of the people were employed full time and 15.52% of respondents were students in employment. 7% of respondents were employed part-time and just 1% of the respondents were unemployed or retired.

4.2 Variables

The indicators (questions) in the first 11 sections of the survey, the core part of research model forming the Exogenous and Endogenous latent variables, were measured using 5-point and 7-point Likert scale. They can be modelled as continuous data and used directly for regression and Factor Analysis. The Demographic data are made up of categorical data such as age, gender, employment status and household income.

4.3 PRINCIPAL COMPONENT ANALYSIS

4.3.1 Assigning Endogenous Latent variables.

Many users use different platforms together, so independent user profiles were created to represent such user behavior. Thus, as explained in the methodology section, EFA was performed on consumer's MSS usage level report (first section in survey) to form Endogenous latent variables, creating user profiles. The EFA results highlighted 4 Eigen values closer to or greater than 1 suggesting 4 components to effectively represent the variance of this section. The eigen values and the scree plot are explained in the appendix section. The factor loadings obtained explains how the MSS choices are loaded in each component:

	PC1	***PC2***	***PC3***	***PC4***
Spotify Premium	0.0226	**0.9189**	-0.1623	-0.0621
Spotify Free	**0.7195**	**-0.5342**	-0.2323	-0.1219
YouTube Free	**0.8195**	0.1429	0.0817	0.0561
YouTube Premium	**-0.7093**	0.1217	-0.0162	-0.1026
Apple Music	0.0367	-0.0999	**0.9726**	-0.0135
Amazon Music	0.0978	-0.0280	-0.0116	**0.9860**

Table 4: Factor loadings of MSS

Factor loadings greater than 0.5 is a safe value to assign a variable to a component and this table highlights those values. From the loadings table it can be observed that both Spotify free and YouTube free with values 0.72 and 0.82 respectively are assigned to the same component RC1, while YouTube premium is negatively loaded in the same component. Spotify Premium, Apple & Amazon Music are loaded in separate components RC2, RC4 and RC3 with values 0.92, 0.97 and 0.985 respectively. Spotify free is negatively loaded with RC2 with a loading value of -0.53 which is much lesser than its value in RC1, so Spotify free will be assigned to RC1 and similarly since YouTube premium is negatively loaded with RC1, a separate latent variable was created for the same in the SEM model.

Thus 5 different Endogenous latent variables (User profiles) were created for the SEM model based on the EFA results as explained in the path diagram *(Fig 4)* in the methodology section.

4.3.2 Assigning Exogenous Latent Variables

As discussed in the methodology section, PCA was performed on the survey results of the next 10 sections (constructs) (PE, EE, PV, PF, SM, SL, PG, VM, FT, MH) of the research model to confirm if the indicators within a construct load under the same component. Exogenous Latent variables for the SEM model were built based on these loadings. The factor loadings of the PCA analysis are shown in *table5*.

	Performance Expectancy (PE)	Effort Expectancy (EE)	Price Value (PV)	Premium-Freemium fit (PF)	Shared subscription (SM)	Social listening (SL)	Perceived Gains (PG)	Broad music taste (VM)	Music Listening Habits (MH)
PE1	**0.91**	0.05	-0.09	-0.06	-0.06	0.07	0.00	-0.01	-0.08
PE2	**0.88**	-0.02	0.00	-0.01	-0.06	0.10	0.10	-0.17	0.04
PE3	**0.80**	-0.05	0.04	0.03	0.01	-0.03	-0.10	0.17	0.08
PE4	**0.81**	-0.02	0.02	0.03	0.06	0.04	-0.10	0.05	-0.02
PE5	**0.64**	0.15	0.06	-0.02	0.08	-0.11	0.16	-0.04	-0.01
EE1	0.05	**0.88**	0.01	-0.06	0.02	-0.09	-0.12	-0.07	0.18
EE2	0.05	**0.78**	0.01	0.10	-0.06	0.01	0.10	0.03	0.04
EE3	-0.03	**0.92**	-0.02	-0.03	0.00	0.02	0.05	-0.05	-0.24
PV1	-0.01	0.06	**0.86**	0.04	0.08	0.01	-0.03	0.02	-0.02
PV2	-0.01	0.06	**0.85**	-0.11	0.05	0.00	0.00	0.06	-0.04
PV3	-0.01	-0.12	**0.91**	0.00	-0.02	0.04	0.08	-0.05	-0.03
PF1	0.01	-0.13	-0.16	**0.77**	0.04	0.07	0.12	0.03	-0.21
PF2	-0.01	-0.01	0.05	**0.90**	0.11	-0.08	0.14	-0.05	-0.13
PF3	-0.05	0.16	0.01	**0.67**	-0.09	0.08	-0.32	0.00	0.32
SM1	0.01	0.01	0.02	0.06	**0.91**	0.09	-0.11	-0.05	-0.02
SM2	-0.04	-0.03	0.05	0.03	**0.94**	0.08	-0.08	0.00	-0.07
SL1	0.12	-0.01	0.01	0.00	0.13	**0.83**	0.00	0.07	0.02
SL2	0.04	-0.03	0.04	0.01	0.07	**0.88**	0.05	0.02	0.02
PG1	0.03	0.05	-0.05	0.00	0.00	-0.08	**0.89**	0.02	-0.13
PG2	-0.04	0.01	0.02	0.03	-0.13	0.12	**0.97**	-0.09	-0.08
PG3	0.06	0.01	0.06	0.02	-0.26	0.12	**0.92**	-0.11	-0.06
VM1	-0.02	-0.04	0.06	0.12	-0.11	0.06	-0.03	**0.72**	0.19
VM2	0.09	-0.03	-0.08	0.03	0.09	-0.17	0.00	**0.73**	0.07
VM3	-0.09	-0.03	0.05	-0.15	-0.02	0.16	-0.16	**0.85**	-0.19
FT1	-0.15	0.22	0.07	0.11	-0.05	0.02	0.49	0.10	0.01
FT2	0.05	0.00	-0.04	0.03	-0.15	0.04	0.34	**0.52**	-0.09
FT3	-0.11	**0.54**	-0.09	-0.12	0.23	0.09	0.15	0.17	0.03
MH1	0.02	-0.11	0.18	0.01	0.01	-0.22	**0.59**	0.07	0.28
MH2	-0.04	-0.05	-0.01	0.13	0.29	0.01	**0.60**	-0.10	0.12
MH3	0.01	-0.08	-0.12	-0.10	0.27	-0.11	**0.62**	0.06	0.07
MH4	-0.06	-0.07	-0.09	-0.16	-0.02	0.26	0.32	-0.06	**0.52**
MH5	0.00	-0.02	-0.04	-0.07	-0.06	0.00	-0.08	0.00	**0.92**

Table 5: Factor Loadings of Indicators (questions) from each construct.

The results of PCA analysis generated 9 eigen values greater than 1 suggesting formation 9 different components to significantly represent the variance of the 10 constructs. The eigen values and the scree plot are showcased in the appendix.

This study considers loadings greater than or equal to 0.5 to assign any variable to a component and those values are highlighted in the table. Indicators(questions) from the sections (constructs) **PE** (*PE1, PE2, PE3, PE4, PE5*), **PV** (*PV1, PV2, PV3*), **PF** (*PF1, PF2, PF3*), **SM** (*SM1, SM2*) and **SL** (*SL1, SL2*) formed 5 individual components for their respective constructs as highlighted in *table5*. Thus, 5 Exogenous latent for the mentioned 5 constructs can be formed using their own indicators.

Indicators from MH and FT did form individual components for their respective constructs like others, FT1 did not load in any component while FT2 and FT3 loaded with indicators from constructs VM and EE respectively, similarly MH1, MH2, MH3 loaded with indicators from PG while MH4 and MH5 loaded together separately in an individual component. These mixed loadings are explained in detailed below:

FT3 discusses a feature where the user's platform can integrate with multiple devices increasing user's ease of use, while EE as a construct discusses the ease of using a MSS. Since all the indicators involved are focused on measuring user's ease of using a MSS, *FT3, EE1, EE2 & EE3* were loaded together to form Latent **EE** in the SEM model.

The construct VM measures user's satisfaction with the music library of their preferred choice of MSS while FT2 measures the perceived importance of podcasts, since podcasts are a part of music library and enhances the variety, *VM1, VM2, VM3 & FT2* were loaded together to form Latent **VM** in the SEM model.

PG1, PG2, PG3, MH1, MH2, MH3 were loaded together in the same component. As discussed in the literature review, both the constructs PG and MH are theoretically based on user's level of involvement with music listening, thus confirming that these constructs are theoretically related. Hence, these six indicators were loaded together to form Latent **PG** in the SEM model. *These results also confirm that people who are more involved and believe in gains of music listening (PG) listen to music during daily activities like Commuting (MH3), Physical workouts or cooking or cleaning (MH2) and tend to listen to music every day in a week (MH1).*

Totally 8 Exogenous latent variables were formed from the results of this PCA analysis as shown in the path diagram *(Fig 4)* in the methodology section.

4.4 RELIABILITY & INTERNAL CONCISTENCY TEST

As discussed in the methodology section, **reliability, consistency, and convergence** of the exogenous latent variables were tested using ***Cronbach's alpha, Composite reliability***, and ***Convergent validity test*** respectively to make sure that the variables are reliable and can explain the variance of the collected data. *Table6* gives a brief of these parameters:

Exogenous Latent Variables	Cronbach's Alpha	Composite-Reliability	AVE
PE	0.90	0.90	0.65
EE	0.81	0.83	0.56
PV	0.88	0.88	0.73
PF	0.72	0.75	0.52
SM	0.85	0.87	0.77
SL	0.88	0.89	0.80
PG	0.87	0.87	0.54
VM	***0.65***	***0.652***	***0.328***

Table 6: Reliability & internal consistency of latent variables.

As mentioned in the methodology section, Cronbach's alpha and composite reliability values were expected to be more than 0.7 for all the latent variables. Except 'VM' every other variable satisfies this condition verifying that the indicators in each respective latent are theoretically consistent and reliable. AVE was expected to be more than 0.5, except 'VM' every other latent variable satisfies this condition ensuring that the variables have the capability to represent more than 50% of the variance of the collected data.

'VM' is the only latent variable with significantly lesser performance values in all the test conducted, but since there are 5 different regressions to be performed in the SEM model, VM was included in the model to check if it has significant influence in at least any one of the regression equations.

4.5 SEM RESULTS

An SEM model was built by regressing 8 exogenous and 5 endogenous latent variables as shown in the Path Diagram (*Fig4*) in the methodology section. The latent variables were formed by factor analysis of indicators that were assigned to each latent based on the results of the PCA analysis. There are 5 separate regressions built in this SEM model and the results of those regressions are shown in *table7*.

**** P-Value significant at 0.1***

	PR1 (*Spotify Free + YouTube Free*)		**PR2 (*Amazon Music*)**		**PR3 (*Spotify Premium*)**		**PR4 (*Apple Music*)**		**PR5 (*YouTube Premium*)**	
	Coeff.	***p-val***	**Coeff.**	***p-val***	**Coeff.**	***p-val***	**Coeff.**	***p-val***	**Coeff.**	***p-val***
PE	**-0.237**	*0.08**	**0.131**	*0.09**	**0.465**	*0.00**	**0.262**	*0.01**	**-0.508**	*0.00**
EE	-0.008	*0.97*	**0.392**	*0.02**	**0.796**	*0.00**	**-0.780**	*0.00**	0.139	*0.50*
PV	**-0.326**	*0.02**	-0.076	*0.49*	**0.426**	*0.01**	-0.082	*0.43*	**0.537**	*0.00**
PF	**0.363**	*0.00**	0.071	*0.29*	**-0.360**	*0.00**	-0.033	*0.60*	**-0.284**	*0.00**
SM	0.064	*0.65*	**-0.209**	*0.07**	0.001	*0.99*	**0.436**	*0.00**	0.062	*0.67*
SL	0.050	*0.64*	0.128	*0.15*	-0.021	*0.86*	**-0.338**	*0.00**	0.158	*0.15*
PG	0.446	*0.12*	0.214	*0.35*	-0.303	*0.33*	0.146	*0.50*	-0.088	*0.76*
VM	**0.429**	*0.04**	**-0.41**	*0.02**	-0.222	*0.33*	**0.453**	*0.01**	0.125	*0.55*

Table 7: SEM Model Results

Coefficients with P-value lesser than or equal to 0.1 were considered to be statistically significant in explaining the user's usage level of their preferred choice of MSS and those values are highlighted with bold numbers while coefficients highlighted in green indicate that it aligns with the construct's hypothesis while the ones highlighted in red does not.

4.5.1 Evaluation of SEM Model.

As mentioned in the methodology section, the SEM model's fit was evaluated using parameters **RMSEA, CFI** and **TLI**. The values are as follows:

- **RMSEA**: ***0.040*** → *Value less than 0.05 indicates very good fit.*
- **CFI**: ***0.951***
- **TLI**: ***0.938***

Both CFI & TLI values indicate that the developed SEM model fits with more than 90% of variance of the collected data.

With the results of the above parameters, it can be safely concluded that the formed SEM model is very close to a saturated model ensuring a high degree of fit and that the model fits with more than 90% of the variance of the collected data. At this point any interpretation done with results of the model will be accurately representative of the observed data.

4.6 ANALYSIS

The coefficients of SEM model are compared and analyzed to understand the relationships of each endogenous variables with the exogenous variables and to interpret the results with respect to the proposed hypothesis under each construct.

4.6.1 Performance Expectancy (PE)

From the above results, PE is the only construct that is significantly related to the usage levels of all the streaming platforms studied, proving that it is the most significant factor that every consumers expect from their MSS. Spotify premium has delivered the best outputs under this aspect as it has the highest coefficient of 0.465 followed by Apple and Amazon at 0.262 and 0.131 respectively, all three supporting this construct's hypothesis, while the free versions of Spotify & YouTube and YouTube premium have failed to meet their user's expectations as they have a negative coefficient at -0.237 and -0.508 respectively failing the construct's hypothesis.

4.6.2 Effort Expectancy (EE)

From the above results, EE is significantly related to the usage levels of platforms Amazon, Apple, and Spotify premium. EE was highly rated by Spotify premium users followed by Amazon with coefficients of 0.796 and 0.392 respectively supporting this construct's hypothesis. Apple music performs very low in this factor compared to others as its coefficient is highly negative with a value of -0.78 failing this construct's hypothesis. Free versions of Spotify & YouTube and YouTube premium are insignificant in their relationships with EE failing this construct's hypothesis, indicating that this construct does not influence usage level of consumers using these platforms.

4.6.3 Price Value (PV)

PV is only significantly related to usage levels of premium and Free versions of both Spotify and YouTube. YouTube premium has the highest user rating followed by Spotify premium with coefficients 0.537 and 0.426 respectively, supporting the construct's hypothesis. The free versions of Spotify & YouTube have very low ratings as expected with a negative coefficient value of -0.326, supporting the hypothesis. Amazon and Apple music are insignificant with this construct, failing the construct's hypothesis and indicating that this construct does not influence usage level of consumers using these platforms.

4.6.4 Premium-freemium fit (PF)

PF has a significant relationship with the usage levels of only the premium and Free versions of Spotify & YouTube. Spotify premium performs the best under this factor with the highest negative coefficient followed by YouTube premium with values -0.36 and -0.284 respectively, supporting the construct's hypothesis. The free versions of Spotify & YouTube perform the worst as expected with positive coefficient value of 0.363, again supporting the hypothesis. Amazon and Apple music are insignificant with this construct, failing the construct's hypothesis thus and indicating that this construct does not influence usage level of consumers using these platforms.

4.6.5 Shared Subscription Model (SM)

SM is only significantly related to the usage levels of Amazon and Apple music. Apple is the best performer under this factor with a positive coefficient of 0.436 while Amazon performs the worst with negative coefficient value of -0209. Thus, Apple music is the only platform supporting this construct's hypothesis while Amazon music has failed the hypothesis by having a negative coefficient. Both the free and the premium versions of Spotify and YouTube have insignificant relationship with the SM factor, failing this construct's hypothesis and indicating that this construct does not influence usage level of consumers using these platforms.

4.6.6 Wide taste in Music (VM)

VM is significantly related to the usage levels of Amazon, Apple music and free versions of Spotify and YouTube. Apple music has the highest user rating under this factor followed by free versions of Spotify & YouTube with coefficients of 0.453 & 0.429 respectively, while Amazon music performs the worst by having a negative coefficient value of -0.41. Thus, Apple music and free versions of Spotify and YouTube support this construct's hypothesis while Amazon music does not. The premium versions of Spotify and YouTube have also failed the hypothesis as they have insignificant relationships with this factor, indicating that this construct does not influence usage level of consumers using these platforms.

4.6.7 Social Listening (SL)

SL is only significantly related to apple music with a negative coefficient of -0.338 indicating poor user ratings. All other platforms are insignificantly related to this construct, indicating that this construct does not influence usage level of consumers using other platforms except Apple. These results indicate that the factor has failed the hypothesis with every platform studied.

4.6.8 Perceived gains of Music listening (PG) & Music Listening Habits (MH)

PG & MH are not significantly related to any of the platform's usage levels, indicating that both MH and PG have failed the hypothesis with every user profile. Thus, it can be concluded that these two factors do not influence the choice or usage level of consumers using any of the platforms considered in this study.

We can observe that all factors except PE are not significantly related to the usage levels of every platform included in this study. This is because users of different platforms have different expectations, so the lack of a significant relationship between a platform and a factor suggests that its users do not have any fixed expectations, while a factor significantly related to a Platform suggests that its users have certain level of expectations for the factor under consideration. As a result, the factors that are significantly related will affect the consumer's choice and usage of an MSS because the consumer expects these factors from a MSS.

Conclusions and discussions are derived based on the discussed interpretation and results.

5. DISCUSSION & CONCLUSION

5.1 DISCUSSIONS

Based on the above results and analysis, a verdict table highlighting the strengths, weaknesses, and the areas requiring development for each platform is proposed (*Table8*). The table is based on the scale mentioned below:

- *Strength* (**S**) → *Served user's expectations by supporting the hypothesis, with a high coefficient value compared to other platforms indicating best performance against the competition.*
- *Weakness* (**W**) → *Failed to serve user's expectations by either rejecting the hypothesis (or) having a very poor user rating.*
- *Need Enhancement* (**NE**) → *Served user's expectations by supporting the hypothesis, but the coefficient value is not the highest among other platforms indicating lower performance than the competition.*
- *Insignificant Relationship* (**IR**) → *The factor is not significantly related to the platform's usage level indicating that its users don't have any expectations.*

Constructs (Factors)	**PR1 (*Spotify Free + YouTube Free*)**	**PR2 (*Amazon Music*)**	**PR3 (*Spotify Premium*)**	**PR4 (*Apple Music*)**	**PR5 (*YouTube Premium*)**
PE	**W**	NE	**S**	NE	**W**
EE	IR	NE	**S**	**W**	IR
PV	**W**	IR	**S**	IR	**S**
PF	**W**	IR	**S**	IR	**S**
SM	IR	**W**	IR	**S**	IR
VM	**S**	**W**	IR	**S**	IR

Table 8: Verdict Table

SL *and* ***PG*** *were dropped as their relationship with all or most of the platforms were insignificant.*

The description of the constructs are as follows:

Construct/Factors	Description/Features
PE	*Recommending song or playlist suiting user's musical taste by using precise music algorithms.*
	Providing sufficient artist/band information.
EE	*Overall ease of using the platform.*
PV	*Attractive and affordable premium packages*
PF	*Showcasing significant difference between the free and premium versions.*
SM	*Attractive shared subscription models*
VM	*Music library with broad range of music collections suiting a wide range of people's musical preferences.*

Table 9: Description of Constructs

5.1.1 Spotify Premium

From (*table8*), it is evident that Spotify premium has the highest number of strengths with no weakness compared to other platforms explaining the reason behind its huge number of premium subscribers (Curry, 2021). Spotify has served its user's expectations in factors such as **PE**, **EE**, **PV,** & **PF** with the highest performance ratings amongst its competition indicating that it provides the best music suggestion algorithms, premium packages and a platform that is most effortless to use. Spotify users do not have significant expectations on the **SM** and **VM** factor, confirming that these factors won't influence consumer's choice or usage of Spotify Premium.

5.1.2 Amazon Music

Amazon music does satisfy its user's expectations under the aspect of **PE and EE** but its user's rating under these areas is still lower than Spotify's suggesting a need for development of its music algorithms and ease of using the platform to become more competitive. Amazon Music users are highly dissatisfied with the variety of music its library offers (**VM**) and its shared subscription model (**SM**), suggesting radical development under these criteria. Regarding the factors **PV** & **PF**, the users do not have significant expectations, confirming that these factors won't influence consumer's choice or usage of Amazon Music.

5.1.3 Apple Music

Apple music satisfies its user's expectations with respect to the **PE** factor but again like Amazon music its ratings are lower than Spotify's suggesting a need for development of its music algorithms to become more competitive. Apple's biggest strength is the variety that its music library offers (**VM**) and its shared subscription models (**SM**). But Apple's biggest weakness is the **EE** factor indicating that its users are really finding it hard to navigate through the platform making music listening experience more effortful and exhausting to its users, suggesting that it needs to make its platform more effortless to use. Apple users do not have significant expectations on **PV** and **PF** factor, confirming that these factors won't influence consumer's choice or usage of Apple Music.

5.1.4 YouTube Premium

This platform's biggest strength is its **PV & PF** factor which has the highest rating among its competitors, indicating that it gives the most attractive and affordable premium packages that significantly enhances the experience compared to the free version. This is because its premium packages are comparatively cheaper than others and it offers ad-free music video streaming along with its music (Pendlebury, 2023) significantly enhancing the premium version's experience. But YouTube has the lowest rating in the most important factor **PE**, suggesting immediate need of developing its music suggestion algorithms. Its users do not have significant expectations on **EE, SM & VM** factors, confirming that these factors won't influence consumer's choice or usage of YouTube Premium.

5.1.5 Spotify & YouTube Free

The above analysis indicates that people using free versions of MSS use both Spotify and YouTube together. People using the free versions are dissatisfied with the most important factors such as **PE, PV & PF** giving them no reasons to opt for a premium version. But people using the premium versions of both these platforms have highly rated these same exact factors. This makes sense because any platform would want their users to opt for a premium version, so both these platforms especially Spotify has identified the factors that its users expect and have delivered the best among the competition explaining the reason behind Spotify having the highest number of premium subscribers (Curry, 2021). Interestingly free version users are happy with the variety of music (**VM**) factor, which may be attributed to the fact that they are using two platforms together giving them access to a wide variety of music. Free version users do not have significant expectations on **EE & VM** factors, confirming that these factors won't influence their choice or usage of Spotify and YouTube's free versions.

5.2 CONCLUSIONS

5.2.1 Factors influencing choice & usage of MSS.

From the above results and discussions, it can be concluded that factors **PE, EE, PV, PF** & **VM** are the most important factors expected by any user from a MSS, thus influencing their choice and usage of MSS. This conclusion is arrived from the fact these factors have established significant relationships with most of the platforms considered in this study. Factors like Perceived gains of Music listening (**PG**), music listening habits of consumers (**MH** & **SL**) do not influence consumer's usage or choice of MSS as they don't have significant relationship with most or none of the platform considered.

5.2.2 Factors influencing consumer's intention to upgrade to a premium version.

Among those significant factors **PE, EE, PV,** & **PF** influence user's intention to opt for a premium versions of MSS. This can be witnessed from the above discussions where users using free versions (*Spotify & YouTube Free*) were highly dissatisfied with these factors, while the users using premium versions (*Spotify & YouTube Premium, Amazon & Apple Music*) were satisfied with these factors.

5.2.3 Strengths and weaknesses of the studied platforms.

Among the premium versions of the platforms Spotify demonstrated more strengths compared to others. Amazon and Apple music served its consumers expectations under PE & EE factors, but still its ratings were lower compared to Spotify suggesting a need for improvement. But Apple performed the best in VM & SM factors compared to others and YouTube's ratings in the PV & PF factor were slightly better than Spotify premium and significantly better than others. But it was Spotify that demonstrated highest ratings in the most important factors like PE & EE and highly competitive ratings in factors like PV & PF which significantly influences both consumer's choice & usage of MSS and their intention to purchase a premium version thus, explaining the reason behind its huge number of user proportion and premium subscribers (Curry, 2021).

5.2.4 Key Contributions

Lot of existing studies have used technology acceptance models like TAM, UTAUT2 to understand the consumer's intention to adopt MSS or to purchase a premium version. Compared with the existing studies, this study applied the UTAUT2 model to identify the factors that strictly influence consumer's choice and usage levels of MSS and used the results to highlight the strengths and weaknesses of the existing platforms. Thus, this study has widened the scope of technology acceptance models by proving that it can also be used to recognize the strengths and weaknesses of the existing technological services or products rather than just using them to understand the user's intention in adopting one.

6. FUTURE SCOPE

The scope of this study can be improved by diversifying the respondents. Music in general is very subjective and each person has their own preferences and likings which could influence their choices of MSS, thus targeting people from specific countries, language or cultural background and age groups might help in identifying the variations in preferences among various groups of people. Increasing the scale of this study will also help in generalizing the results obtained, which could help industries come up with global strategies.

The methodology of this study can be applied to other subscription-based services like the online video streaming platforms, software subscriptions etc., to identify the factors that influence consumer's choices or to highlight the strengths and weaknesses of the existing platforms.

7. LIMITATIONS

There are many statistical and theoretical limitations to this study. Firstly, this study was focused on people who were mostly master's students or graduate employees who are at their early or mid-twenties, but as mentioned in the introduction section teenagers from the age of 15 also contribute to a major proportion of MSS usage whom this study missed to include making the study not completely representative of population responsible for major usage of MSS.

The developed SEM model was based on a biased sample. For Ex: Apple and Amazon music users contributed to just 10% and 14% of the data collected, while the remaining were either Spotify or YouTube users making this study biased and resulting in Apple and Amazon music having insignificant relationships with many important factors like EE, PV & PF.

As mentioned in the Introduction section the platforms considered here offers very different service models like Apple offering cloud storage to its premium users (Apple, 2023), Amazon music being complementary to Amazon prime subscribers (Amazon, 2023) and YouTube offering ad-free video streaming along with ad-free music (YouTube, 2023) while Spotify being the only platform offering only ad-free music to its premium subscribers (Spotify, 2023), (Pendlebury, 2023). This research model did not consider those non-music related services missing to understand the influence of such diverse service models on consumer's choices of MSS.

REFERENCES

(Larsen et al., 2009)

Larsen, G., Lawson, R. and Todd, S. 2009. The consumption of music as self-representation in social interaction. *Australasian Marketing Journal (AMJ)*. **17**(1), pp.16–26.

(Albright, 2015)

Albright, D. 2015. The evolution of music consumption: How we got here. *MUO*. [Online]. [Accessed 17 August 2023]. Available from: https://www.makeuseof.com/tag/the-evolution-of-music-consumption-how-we-got-here/.

(Arditi, 2014)

Arditi, D. 2014. ITunes: Breaking barriers and building walls. *Popular Music & Society*. **37**(4), pp.408–424.

(The Editors of Encyclopedia Britannica, 2023)

The Editors of Encyclopedia Britannica 2023. Napster. *Encyclopedia Britannica*.

(IFPI.org)

IFPI.org. Ifpi global music report 2023. *Ifpi.org*. [Online]. [Accessed 17 August 2023]. Available from: https://globalmusicreport.ifpi.org/.

(Curry, 2021)

Curry, D. 2021. Music streaming app revenue and usage statistics (2023). *Business of Apps*. [Online]. [Accessed 17 August 2023]. Available from: https://www.businessofapps.com/data/music-streaming-market/.

(Pendlebury, 2023)

Pendlebury, T. 2023. Best music streaming service of 2023. *CNET*. [Online]. [Accessed 17 August 2023]. Available from: https://www.cnet.com/tech/services-and-software/best-music-streaming-service/.

(Armstrong, 2020)

Armstrong, M. 2020. The world's most popular music streaming services. *Statista*. [Online]. [Accessed 17 August 2023]. Available from: https://www.statista.com/chart/20826/music-streaming-services-with-most-subscribers-global-fipp/.

(Andy, 2021)

Andy, G. 2021. Spotify vs. Youtube Music: Which is better? *Headphonesty*. [Online]. [Accessed 17 August 2023]. Available from: https://www.headphonesty.com/2021/03/spotify-vs-youtube-music/.

(Susic, 2022)
Susic, P. 2022. 40+ fascinating music streaming statistics (2023 updated). *HeadphonesAddict*. [Online]. [Accessed 17 August 2023]. Available from: https://headphonesaddict.com/music-streaming-statistics/.

(Ferjan, 2022)
Ferjan, M. 2022. 30+ people listening to music statistics & trends (2023). *HeadphonesAddict*. [Online]. [Accessed 18 August 2023]. Available from: https://headphonesaddict.com/listening-to-music-statistics/.

(Santangelo, 2022)
Santangelo, R. 2022. Music streaming market share and revenue statistics: Details on the biggest music streaming services. *SiriusXM Music for Business*. [Online]. [Accessed 6 September 2023]. Available from: https://sxmbusiness.com/music-streaming-market-share-and-revenue-statistics/.

(Grandviewresearch.com)
Anon n.d. Music streaming market size, share & trends analysis report by service (on-demand streaming, live streaming), by platform (apps, browsers), by end-use (commercial, individual), by content type, by region, and segment forecasts, 2023 - 2030. *Grandviewresearch.com*. [Online]. [Accessed 6 September 2023b]. Available from: https://www.grandviewresearch.com/industry-analysis/music-streaming-market.

(Wikipedia contributors, 2023a)
Wikipedia contributors 2023a. Amazon Music. *Wikipedia, The Free Encyclopedia*. [Online]. Available from: https://en.wikipedia.org/w/index.php?title=Amazon_Music&oldid=1169406511.

(Wikipedia contributors, 2023a)
Wikipedia contributors 2023b. History of iTunes. *Wikipedia, The Free Encyclopedia*. [Online]. Available from: https://en.wikipedia.org/w/index.php?title=History_of_iTunes&oldid=1169467817.

(Wikipedia contributors, 2023b)
Wikipedia contributors 2023c. Spotify. *Wikipedia, The Free Encyclopedia*. [Online]. Available from: https://en.wikipedia.org/w/index.php?title=Spotify&oldid=1175092576.

(Wikipedia contributors, 2023c)
Wikipedia contributors 2023d. Tencent Music. *Wikipedia, The Free Encyclopedia*. [Online]. Available from: https://en.wikipedia.org/w/index.php?title=Tencent_Music&oldid=1171438086.

(Akinnuwesi et al., 2022)
Akinnuwesi, B.A., Uzoka, F.-M.E., Fashoto, S.G., Mbunge, E., Odumabo, A., Amusa, O.O., Okpeku, M. and Owolabi, O. 2022. A modified UTAUT model for the acceptance and use of digital technology for tackling COVID-19. *Sustainable Operations and Computers*. **3**, pp.118–135.

(Barata and Coelho, 2021)
Barata, M.L. and Coelho, P.S. 2021. Music streaming services: understanding the drivers of customer purchase and intention to recommend. *Heliyon*. **7**(8), p.e07783.

(Bian and Moutinho, 2009)
Bian, X. and Moutinho, L. 2009. An investigation of determinants of counterfeit purchase consideration. *Journal of business research*. **62**(3), pp.368–378.

(Cesareo and Pastore, 2014)
Cesareo, L. and Pastore, A. 2014. Consumers' attitude and behavior towards online music piracy and subscription-based services. *The journal of consumer marketing*. **31**(6/7), pp.515–525.

(Chen et al., 2022)
Chen, C.C., Leon, S. and Nakayama, M. 2022. Are you hooked on paid music streaming?: An investigation into the Millennial generation. *International journal of e-business research*. **14**(1), pp.1–20.

(Chu and Lu, 2007)
Chu, C.-W. and Lu, H.-P. 2007. Factors influencing online music purchase intention in Taiwan: An empirical study based on the value-intention framework. *Internet research*. **17**(2), pp.139–155.

(Davis, 1989)
Davis, F.D. 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly: management information systems*. **13**(3), p.319.

(Dodds, 1991)
Dodds, W.B. 1991. In search of value: how price and store name information influence buyers′ product perceptions. *The journal of consumer marketing*. **8**(2), pp.15–24.

(Hamari et al., 2020)
Hamari, J., Hanner, N. and Koivisto, J. 2020. 'Why pay premium in freemium services?' A study on perceived value, continued use and purchase intentions in free-to-play games. *International journal of information management*. **51**(102040), p.102040.

(Hampton-Sosa, 2017)
Hampton-Sosa, W. 2017. An exploration of essential factors that influence music streaming adoption and the intention to engage in digital piracy. *International journal of electronic commerce studies*. **8**(1).

(Hampton-Sosa, 2019)
Hampton-Sosa, W. 2019. The access model for music and the effect of modification, trial, and sharing usage rights on streaming adoption and piracy. *Journal of theoretical and applied electronic commerce research*. **14**(3), pp.126–155.

(Iyengar et al., 2020)
Iyengar, R., Park, Y.-H. and Yu, Q. 2020. The impact of subscription programs on customer purchases. *SSRN Electronic Journal*.

(Kim and Malhotra, 2005)
Kim, S.S. and Malhotra, N.K. 2005. A longitudinal model of continued IS use: An integrative view of four mechanisms underlying postadoption phenomena. *Management science*. **51**(5), pp.741–755.

(Kuei and Madu, 2003)
Kuei, C.-H. and Madu, C.N. 2003. Customer-centric six sigma quality and reliability management. *International journal of quality & reliability management*. **20**(8), pp.954–964.

(Kwong and Park, 2008)
Kwong, S.W. and Park, J. 2008. Digital music services: consumer intention and adoption. *Service industries journal*. **28**(10), pp.1463–1481.

(Li and Cheng, n.d.)
Li, Z. and Cheng, Y. n.d. From free to fee: Exploring the antecedents of consumer intention to switch to paid online content. *Jecr.org*. [Online]. [Accessed 23 August 2023]. Available from: http://ojs.jecr.org/jecr/sites/default/files/15_4_p02.pdf.

(Stratton and Zalanowski, 2003)
Stratton, V.N. and Zalanowski, A.H. 2003. Daily music listening habits in college students: Related moods and activities. *Psychology and education*. **40**(1), pp.1–11.

(Styvén, 2010)
Styvén, M.E. 2010. The need to touch: Exploring the link between music involvement and tangibility preference. *Journal of business research*. **63**(9–10), pp.1088–1094.

(Ueda et al., 2013)
Ueda, T., Suzukamo, Y., Sato, M. and Izumi, S.-I. 2013. Effects of music therapy

on behavioral and psychological symptoms of dementia: a systematic review and meta-analysis. *Ageing research reviews*. **12**(2), pp.628–641.

(van der Heijden, 2004)
van der Heijden 2004. User Acceptance of Hedonic Information Systems. *MIS quarterly: management information systems*. **28**(4), p.695.

(Venkatesh et al., 2003)
Venkatesh, Morris, Davis and Davis 2003. User acceptance of information technology: Toward a unified view. *MIS quarterly: management information systems*. **27**(3), p.425.

(Venkatesh et al., 2012)
Venkatesh, Thong and Xu 2012. Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS quarterly: management information systems*. **36**(1), p.157.

(Venkatesh and Davis, 1996)
Venkatesh, V. and Davis, F.D. 1996. A model of the antecedents of perceived ease of use: Development and test. *Decision sciences*. **27**(3), pp.451–481.

(Venkatesh and Davis, 2000)
Venkatesh, V. and Davis, F.D. 2000. A theoretical extension of the Technology Acceptance Model: Four longitudinal field studies. *Management science*. **46**(2), pp.186–204.

(Wagner et al., 2014)
Wagner, T.M., Benlian, A. and Hess, T. 2014. Converting freemium customers from free to premium—the role of the perceived premium fit in the case of music as a service. *Electronic Markets*. **24**(4), pp.259–268.

(Guerra and Fernandes, 2019)
Guerra, J. and Fernandes, T. 2019. Drivers and deterrents of music streaming services purchase intention. *International journal of electronic business*. **15**(1), p.21.

(Dörr et al., 2013)
Dörr, J., Wagner, T., Benlian, A. and Hess, T. 2013. Music as a service as an alternative to music piracy?: An empirical investigation of the intention to use music streaming services. *Business & information systems engineering*. **5**(6), pp.383–396.

(Henseler et al., 2009)
Henseler, J., Ringle, C.M. and Sinkovics, R.R. 2009. The use of partial least squares path modeling in international marketing *In*: *Advances in International Marketing*. Emerald Group Publishing Limited, pp.277–319.

(Hair et al., 2013)
Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. 2013. *A primer on partial least squares structural equation modeling (pls-Sem)*. Christchurch, New Zealand: Sage Publications.

(Fornell and Larcker, 1981)
Fornell, C. and Larcker, D.F. 1981. Evaluating structural equation models with unobservable variables and measurement error. *JMR, Journal of marketing research*. **18**(1), p.39.

(Brown, 2014)
Brown, T.A. 2014. *Confirmatory factor analysis for applied research*. New York, NY, USA: Guilford Publications.

(Cattell, 1966)
Cattell, R.B. 1966. The scree test for the number of factors. *Multivariate behavioral research*. **1**(2), pp.245–276.

(Kaiser, 1960)
Kaiser, H.F. 1960. The application of electronic computers to factor analysis. *Educational and psychological measurement*. **20**(1), pp.141–151.

(Hair et al., 2021)
Hair, J.F., Jr, Hult, G.T.M., Ringle, C.M., Sarstedt, M., Danks, N.P. and Ray, S. 2021. *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook* 1st ed. Cham, Switzerland: Springer Nature.

(UCLA.edu)
UCLA.edu. Introduction to Structural Equation Modeling (SEM) in R with lavaan. *Ucla.edu*. [Online]. [Accessed 29 August 2023]. Available from: https://stats.oarc.ucla.edu/r/seminars/rsem/.

(Qualtrics, 2015)
Qualtrics 2015. Qualtrics XM - experience management software. *Qualtrics*. [Online]. [Accessed 2 September 2023]. Available from: https://www.qualtrics.com.

(Rosseel, n.d.)
Rosseel, Y. n.d. The lavaan project. *Ugent.be*. [Online]. [Accessed 3 September 2023]. Available from: https://lavaan.ugent.be/tutorial/cfa.html.

(Apple, 2023)
Apple 2023. Apple music. *Apple (United Kingdom)*. [Online]. [Accessed 8 September 2023]. Available from: https://www.apple.com/uk/apple-music/.

(Amazon, 2023)

Amazon 2023. *Amazon.co.uk*. [Online]. [Accessed 10 September 2023]. Available from: https://www.amazon.co.uk/music/unlimited.

(YouTube, 2023)

YouTube 2023. Before you continue to YouTube. [Accessed 10 September 2023]. Available from: https://www.youtube.com/premium.

(Spotify, 2023)

Spotify 2023. Spotify Premium - Get 3 months free - Spotify (UK). *Spotify*. [Online]. [Accessed 10 September 2023]. Available from: https://www.spotify.com/uk/premium/.

8. APPENDIX

8.1 QUESTIONNIARE

8.1.1 Section 1

1. How often do you use the following Music Streaming Services for music listening, please rate every option based on your frequency of usage.

	Very Frequently	Frequently	Regularly	Occasionally	Never or Almost Never
Spotify Premium	○	○	○	○	○
Spotify Free	○	○	○	○	○
YouTube Free	○	○	○	○	○
YouTube Premium	○	○	○	○	○
Apple Music	○	○	○	○	○
Amazon Music	○	○	○	○	○
Others - Please Specify	○	○	○	○	○

8.2.2 Section 2

(All the questions were answered using a 7 point Likert Scale)

Performance Expectancy (PE)

Music streaming services:

1. have enhanced my playlists by recommending the right set of music suiting my musical taste.
2. recommends the perfect playlists or songs suitable for various occasions or moods, for example Workout playlist, travelling playlist or Romantic Playlists etc.
3. have introduced me to a diverse range of music genres I didn't knew I would like listening to, expanding my musical horizons.
4. provides me with enough information about the artists or bands that I follow.
5. have significantly improved the overall music listening experience.

Effort Expectancy (EE)

Music streaming services:

1. makes music listening sessions effortless.
2. makes it effortless to create and maintain the playlists.
3. User-interface makes it effortless to navigate through its features and music collections.

Price Value (PV)

My most preferred music streaming service

1. offers a variety of attractive premium packages.
2. premium subscription provides good value for money.

3. premium version is affordable and cheap.

Premium-Freemium Fit (PF)

1. I prefer listening to ads and facing other restrictions than paying for a music streaming service.
2. Listening to advertisements is a small price to pay for a free service.
3. The free and premium services of my preferred music streaming service are very similar.

Shared Subscription Model (SM)

1. I would like to subscribe or continue using a shared subscription model with my friends or family members in the future.
2. Shared subscription plans offer as much freedom and usability as individual plans, for less money.

Social Listening (SL)

I like:

1. sharing my playlist with my friends or family.
2. creating playlists in collaboration with my friends or family.

Perceived Gains of Music Listening (PG)

1. Listening to music gives me great pleasure and joy.
2. Listening to music is motivating and increases my productivity and performance.
3. Listening to music helps me maintain good mental health.

Wide Taste in Music (VM)

1. I like listening to remixes, mashups, and cover songs made by non-established artists.
2. I listen to music from a wide variety of languages or cultural backgrounds.
3. I like to have the option of watching videos of the songs that I listen to.

Features (FT)

1. Music with high audio quality is very important to me.
2. Availability of quality podcasts is very important to me.
3. A music streaming service's application should integrate seamlessly with all my devices. For example, controlling the music playing in my laptop from my phone or vice-versa.

Music Listening Habits (MH)

I listen to music:

1. every day in a week.
2. during any physical activities like workouts, running or cooking, cleaning etc.
3. during my daily commute or while traveling on vacations.
4. while studying or working.
5. before going to sleep.

8.2.3 Section 3 (Type in Question)

Room for Enhancement

Do you think there is room for enhancing the music listening service provided by your preferred music streaming service? In what way would you like it to improve?

8.2.4 Section 4 (Demographic Info)

Please Select your Age:

- Under 18
- 18 – 24
- 25 – 34
- 35 – 44
- 45 – 54
- 55 or Older

Please select you Gender:

- Male
- Female
- Prefer not to say

Please select your Employment Status

- Employed Full Time
- Employed Part Time
- Student not employed
- Student & employed
- Unemployed & Retired

Please select your household Income. (you may skip this question if you don't wish to answer)

- £20,000 or Less
- £20,001 - £40,000
- £40,001 - £60,000

- £60,001 - £80,000
- £80,001 or more

Survey Link
https://leedsubs.eu.qualtrics.com/jfe/form/SV_eyujFm2PtFrci0e

8.3 CODE

8.3.1 PCA Analysis

EFA analysis to identify User profiles, based on which Endogenous Latent Variables will be formed.

```
#---------------------------------------------------------------------------------
#Section - 1 EFA on consumer's MSS usage levels reported to identify user profiles
#(Endogenous Latent variables)
#---------------------------------------------------------------------------------
data <- read.csv("05_08_2023_1.csv", header=TRUE)
profile <- data[1:6]
library(dplyr)
# Function to recode Likert scale values to numerical values
likert_to_numerical <- function(x) {
  recode(x,
         "Very Frequently" = 5,
         "Frequently" = 4,
         "Regularly" = 3,
         "Occasionally" = 2,
         "Never or Almost Never" = 1)
}
# Applying the function
profile[1:6] <- profile[1:6] %>% mutate_all(likert_to_numerical)

# PCA & scale to unit variance
latent_ca <- prcomp(profile[1:6], scale = TRUE, center = TRUE)
summary(latent_ca)
latent_ca$x
# get eiganvalues using SD2
latent_ca$sdev ^ 2

# scree plot (barplot)
plot(latent_ca)
# normal scree plot (line)
```

```
plot(latent_ca, type="line")
# PCA biplot
biplot((latent_ca))
# Get scores
latent_ca$x
loadings <- latent_ca$rotation
class(loadings)
write.csv(loadings, file = "profile_loadings.csv", row.names = TRUE)

# ------ PCA Rotation ------
# using the principal functiuon in the psych package
install.packages("psych")
install.packages("GPArotation")
library(psych)
library(GPArotation)
latent_ca1 <- principal(profile[1:6], nfactors = 4, rotate="none")
summary(latent_ca1)
loadings <- latent_ca1$loadings

# Using promax to get components
latent_ca3 <- principal(profile[1:6], nfactors = 4, rotate="promax")
loadings <- latent_ca3$loadings
```

PCA Analysis on the next 10 sections of the questionnaire, results based on which Exogenous Latent Variables will be formed.

```
#-------------------------------------------------------------------------------------
#Section 2-11 PCA analysis of constructs to form Exogenous Latent Variables
#-------------------------------------------------------------------------------------
latent <- read.csv("05_08_2023_1.csv", header=TRUE)
latent1 <- latent[8:39]



#latent1[20:25] <- NULL
library(dplyr)
# Function to recode Likert scale values to numerical values
likert_to_numerical <- function(x) {
  recode(x,
         "Strongly disagree" = 1,
```

```
         "Disagree" = 2,
         "Somewhat disagree" = 3,
         "Neither agree nor disagree" = 4,
         "Somewhat agree" = 5,
         "Agree" = 6,
         "Strongly agree" = 7)
}
# Apply the function to all columns using mutate_all
latent1[1:32] <- latent1[1:32] %>% mutate_all(likert_to_numerical)
# PCA & scale to unit variance
latent_ca <- prcomp(latent1[1:32], scale = TRUE, center = TRUE)
summary(latent_ca)
latent_ca$x
# get eiganvalues using SD2
latent_ca$sdev ^ 2
# scree plot (barplot)
plot(latent_ca)
# normal scree plot (line)
plot(latent_ca, type="line")
# PCA biplot
biplot((latent_ca))
# Get scores
latent_ca$x

# ------ PCA Rotation ------
# using the principal functiuon in the psych package
library(psych)
library(GPArotation)
summary(prcomp(latent1[1:32]))
latent_ca1 <- principal(latent1[1:32], nfactors = 9, rotate="none")
loadings <- latent_ca1$loadings

# Using promax to get components
latent_ca3 <- principal(latent1[1:32], nfactors = 9, rotate="promax")
loadings <- latent_ca3$loadings

write.csv(loadings, file = "pilot_study_loadings.csv", row.names = TRUE)
```

8.3.2 Cronbach's Alpha, Composite Reliability & AVE test.

```
#--------------------------------------------------------------------------------------
# Cronbach's alpha, composite reliability and AVE test to measure reliability and
consistency
# of Exogenous Latent Variables
#--------------------------------------------------------------------------------------
library(psych)
library(semTools)
library(dplyr)

data <- read.csv("05_08_2023_1.csv", header=TRUE)
data1 <- data

# Function to recode Likert scale values to numerical values
likert_to_numerical <- function(x) {
  recode(x,
         "Very Frequently" = 5,
         "Frequently" = 4,
         "Regularly" = 3,
         "Occasionally" = 2,
         "Never or Almost Never" = 1)
}


# Apply the function to all columns using mutate_all
data1[1:7] <- data1[1:7] %>% mutate_all(likert_to_numerical)

# Function to recode Likert scale values to numerical values
likert_to_numerical <- function(x) {
  recode(x,
         "Strongly disagree" = 1,
         "Disagree" = 2,
         "Somewhat disagree" = 3,
         "Neither agree nor disagree" = 4,
         "Somewhat agree" = 5,
         "Agree" = 6,
```

```
        "Strongly agree" = 7)
}

# Apply the function to all columns using mutate_all
data1[8:39] <- data1[8:39] %>% mutate_all(likert_to_numerical)

PE <- data1[7:11]
EE <- data1[12:14]
EE$FT3 <- data1$FT3
PV <- data1[15:17]
PF <- data1[18:20]
SI <- data1[21:22]
SL <- data1[23:24]
PG <- data1[25:27]
PG$MH1 <- data1$MH1
PG$MH2 <- data1$MH2
PG$MH3 <- data1$MH3
VM <- data1[28:30]
VM$FT2 <- data1$FT2

# Calculate Cronbach's alpha
 alpha(PE)
 alpha(EE)
 alpha(PV)
 alpha(PF)
 alpha(SI)
 alpha(SL)
 alpha(PG)
 alpha(VM)

#-----------------------Composite reliability & AVE test------------------------------
----

library(lavaan)
#one factor three items, default marker method
PE <- 'PE  =~ PE1 + PE2 + PE3 + PE4 + PE5'
fit_PE <- cfa(PE, data=data1, std.lv = TRUE)
summary(fit_PE)
compRelSEM(fit_PE)
```

```
AVE(fit_PE)
reliability()

EE <- 'EE =~ EE1 + EE2 + EE3 + FT3'
fit_EE <- cfa(EE, data=data1)
summary(fit_EE)
compRelSEM(fit_EE)
AVE(fit_EE)

PV <- 'PV =~ PV1 + PV2 + PV3'
fit_PV <- cfa(PV, data=data1)
summary(fit_PV)
compRelSEM(fit_PV)
AVE(fit_PV)

PF <- 'PF =~ PF1 + PF2 + PF3'
fit_PF <- cfa(PF, data=data1)
summary(fit_PF)
compRelSEM(fit_PF)
AVE(fit_PF)

SI <- 'SI =~ SI1 + SI2'
fit_SI <- cfa(SI, data=data1)
summary(fit_SI)
compRelSEM(fit_SI)
AVE(fit_SI)

SL <- 'SL =~ SL1 + SL2'
fit_SL <- cfa(SL, data=data1)
summary(fit_SL)
compRelSEM(fit_SL)
AVE(fit_SL)

PG <- 'PG =~ PG1 + PG2 + PG3 + MH1 + MH2 + MH3'
fit_PG <- cfa(PG, data=data1)
summary(fit_PG)
compRelSEM(fit_PG)
AVE(fit_PG)
```

```
VM <- 'VM =~ VM1 + VM2 + VM3 + FT2'
fit_VM <- cfa(VM, data=data1)
summary(fit_VM)
compRelSEM(fit_VM)
AVE(fit_VM)
```

8.3.3 STRUCTURAL EQUATION MODELLING (SEM)

```
#-------------------------------------------------------------------------------------
#Structural Equation Modelling (SEM)
#-------------------------------------------------------------------------------------
library(dplyr)
data <- read.csv("05_08_2023_1.csv", header=TRUE)
data1 <- data
#-----------------Converting likert scale to numbers----------------------------------
-------
# Function to recode Likert scale values to numerical values
likert_to_numerical <- function(x) {
  recode(x,
         "Very Frequently" = 5,
         "Frequently" = 4,
         "Regularly" = 3,
         "Occasionally" = 2,
         "Never or Almost Never" = 1)
}

# Apply the function to all columns using mutate_all
data1[1:7] <- data1[1:7] %>% mutate_all(likert_to_numerical)

# Function to recode Likert scale values to numerical values
likert_to_numerical <- function(x) {
 recode(x,
         "Strongly disagree" = 1,
         "Disagree" = 2,
         "Somewhat disagree" = 3,
         "Neither agree nor disagree" = 4,
         "Somewhat agree" = 5,
```

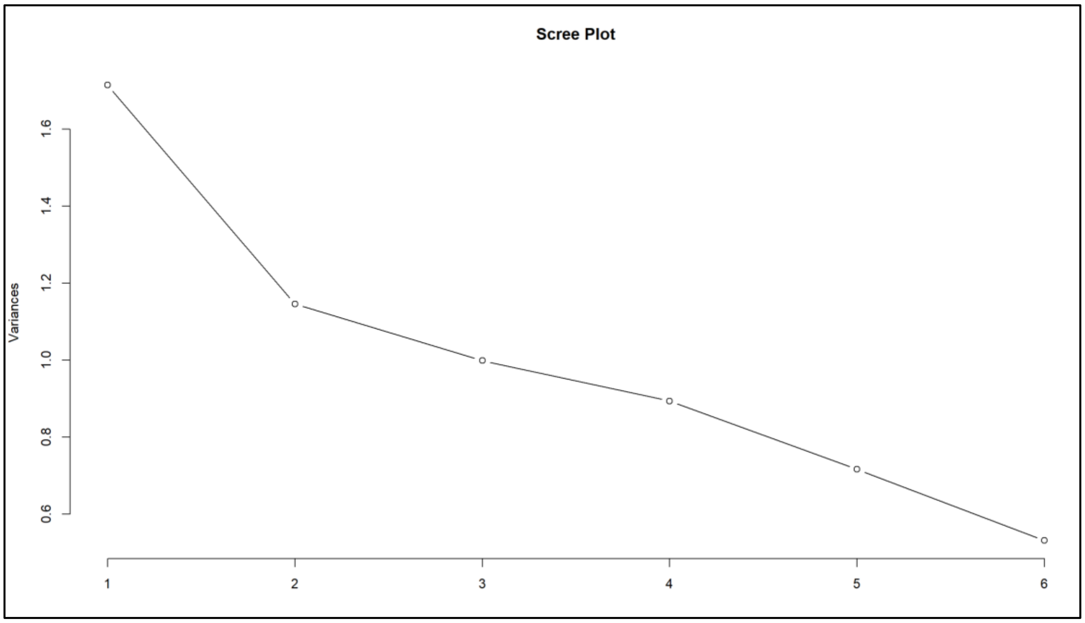
```
        "Agree" = 6,
        "Strongly agree" = 7)
}



# Apply the function to all columns using mutate_all
data1[8:39] <- data1[8:39] %>% mutate_all(likert_to_numerical)

#---------------------Bringing all the variables under one single scale (0-1)-----------------
# Endogenous variables (consumer's usage level)
multiply_by_one_fifth <- function(df) {
  df * (1/5)
}

data1[1:7] <- multiply_by_one_fifth(data1[1:7])

# Exogenous Variable (Consumer's measure of agrrement with the construct's statement)
multiply_by_one_seventh <- function(df) {
  df * (1/7)
}
data1[8:39] <- multiply_by_one_seventh(data1[8:39])

#-------------------------------------SEM--------------------------------------------
library(lavaan)
#removing omitted variables
data1$MH5 <- NULL
data1$MH4 <- NULL
data1$Others <- NULL



#SEM Model
m6c <- '
# measurement model
PE =~ PE1 + PE2 + PE3 + PE4
EE =~ EE1 + EE2 + EE3 + FT3
PV =~ PV1 + PV2 + PV3
```

```
PF =~ PF1 + PF2 + PF3
SM =~ SM1 + SM2
SL =~ SL1 + SL2
PG =~ PG1 + PG2 + PG3 + MH1 + MH2 + MH3
VM =~ VM1 + VM2 + VM3 + FT2
PR1 =~ Spotify.Free + YouTube.Free
PR2 =~ 1*Amazon.Music
PR3 =~ 1*Spotify.Premium
PR4 =~ 1*Apple.Music
PR5 =~ 1*YouTube.Premium

# regressions
PR1 ~ PE + EE + PV + PF + SM + SL + PG + VM
PR2 ~ PE + EE + PV + PF + SM + SL + PG + VM
PR3 ~ PE + EE + PV + PF + SM + SL + PG + VM
PR4 ~ PE + EE + PV + PF + SM + SL + PG + VM
PR5 ~ PE + EE + PV + PF + SM + SL + PG + VM

#Co-variances
PG2 ~~ PG3
PE1 ~~ PE2
PF1 ~~ PF3
PG3 ~~ MH3
PG2 ~~ MH3
'

#SEM results
fit6c <- sem(m6c, data=data1)
summary(fit6c, standardized=TRUE, fit.measures=TRUE, rsquare=TRUE)
modindices(fit6c,sort=TRUE)
```

8.4 RESULTS

8.4.1 Scree plot and Eigen values of EFA analysis to form User profiles.

```
> latent_ca$sdev ^ 2
[1] 1.7148666 1.1456450 0.9987082 0.8935185 0.7159735 0.5312883
```

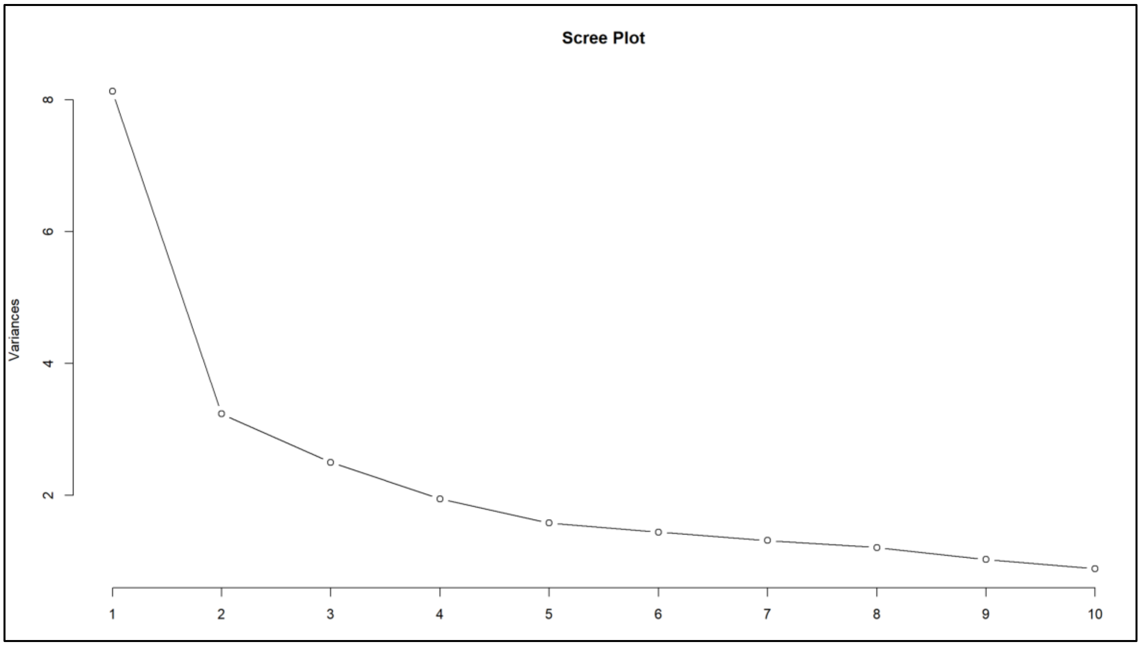


8.4.2 Factor Loadings of EFA results

A	B	C	D	E	F	G	H
	PC1	PC2	PC3	PC4		0.5	**upper bound**
Spotify.Premium	0.022572376	0.918909137	-0.162257731	-0.062085396	1	-0.5	**lower bound**
Spotify.Free	0.719490814	-0.534156091	-0.232344138	-0.121865252	2	2	
YouTube.Free	0.819477602	0.142915387	0.081681404	0.056102584	1		
YouTube.Premium	-0.709312389	0.121696295	-0.01617213	-0.102633886	1		
Apple.Music	0.036744919	-0.099903104	0.972580691	-0.013546706	1		
Amazon.Music	0.097753359	-0.028038585	-0.011643593	0.985966344	1		

8.4.3 Scree plot and Eigen values of PCA analysis to form Exogenous Latent Variables

```
> latent_ca$sdev ^ 2
 [1] 8.1278189 3.2338772 2.4989816 1.9453415 1.5772489 1.4403489 1.3124555 1.2056585 1.0252169
[10] 0.8831217 0.7800740 0.7476028 0.6723363 0.6482413 0.5848187 0.5468878 0.5117540 0.4783144
[19] 0.3918258 0.3743738 0.3652333 0.3597857 0.3461346 0.3139387 0.2990345 0.2570388 0.2176679
[28] 0.1998349 0.1943543 0.1811555 0.1566815 0.1228419
```



8.4.4 Factor Loadings of PCA analysis

A	B	C	D	E	F	G	H	I	J	K	L	M	N
	PE	EE	PV	PF	SM	SL	PG	VM	MH			0.5	*upper bound*
PE1	0.905347	0.05495	-0.08863	-0.05714	-0.06008	0.069611	0.001646	-0.01238	-0.07703	1		-0.5	*lower bound*
PE2	0.883976	-0.01786	-0.00472	-0.00645	-0.05913	0.103316	0.100085	-0.16911	0.036493	1		1	
PE3	0.797791	-0.04807	0.042702	0.030623	0.014995	-0.02884	-0.10041	0.168377	0.079282	1	**Key**		
PE4	0.810917	-0.01876	0.022412	0.034507	0.056185	0.039773	-0.10341	0.05286	-0.02078	1	**PE**	*Performance Expectancy*	
PE5	0.643079	0.145924	0.057479	-0.01705	0.083834	-0.10757	0.159802	-0.03569	-0.00782	1	**EE**	*Effort Expectancy*	
EE1	0.0515	0.883386	0.007554	-0.06177	0.015892	-0.08678	-0.11691	-0.06662	0.184722	1	**PV**	*Price-Value*	
EE2	0.054124	0.784935	0.014386	0.099893	-0.05802	0.014974	0.096526	0.031603	0.041005	1	**PF**	*Premium Vs Freemium Fit*	
EE3	-0.02657	0.923282	-0.01705	-0.03121	-0.00412	0.0225	0.04724	-0.05025	-0.23878	1	**SM**	*Shared Subscription Model*	
PV1	-0.00968	0.05853	0.861613	0.042147	0.076962	0.011666	-0.02745	0.021432	-0.0204	1	**SL**	*Social Listening*	
PV2	-0.01095	0.062097	0.851923	-0.10578	0.048122	0.003166	0.004315	0.058812	-0.04249	1	**VM**	*Wide Musical Taste*	
PV3	-0.01007	-0.11526	0.912739	-0.00141	-0.02492	0.041939	0.080346	-0.04666	-0.02521	1	**FT**	*Features*	
PF1	0.009825	-0.13354	-0.16445	0.76609	0.035844	0.073479	0.118324	0.031169	-0.20942	1	**MH**	*Music Listening habits*	
PF2	-0.0072	-0.00737	0.046943	0.896762	0.105956	-0.07605	0.136657	-0.04619	-0.12655	1	**PG**	*Percieved gains of listening to music*	
PF3	-0.04878	0.16167	0.010366	0.668367	-0.09298	0.082471	-0.31529	-0.00127	0.319525	1			
SI1	0.011691	0.014437	0.024774	0.062098	0.914207	0.090437	-0.1082	-0.05096	-0.02096	1			
SI2	-0.03868	-0.02764	0.053546	0.032021	0.938711	0.083203	-0.08202	-0.00209	-0.07457	1			
SL1	0.116232	-0.01432	0.009965	-6.86E-05	0.125546	0.829518	0.00434	0.072073	0.022867	1			
SL2	0.035631	-0.02645	0.039513	0.009624	0.073223	0.882254	0.048087	0.02077	0.022099	1			
PG1	0.02859	0.046566	-0.05095	0.004425	-0.00074	-0.08427	0.889093	0.024478	-0.12571	1			
PG2	-0.04217	0.009892	0.021346	0.031618	-0.13387	0.119548	0.966341	-0.08733	-0.0815	1			
PG3	0.063645	0.014115	0.058159	0.019248	-0.26106	0.124702	0.916733	-0.11249	-0.06245	1			
VM1	-0.01787	-0.04176	0.064029	0.123437	-0.10783	0.058271	-0.02915	0.717737	0.185821	1			
VM2	0.092085	-0.02887	-0.08486	0.034983	0.091171	-0.16782	-0.00169	0.7302	0.074448	1			
VM3	-0.09059	-0.0313	0.04735	-0.14961	-0.02141	0.15856	-0.16425	0.849867	-0.18643	1			
FT1	-0.14746	0.218922	0.074192	0.113821	-0.05212	0.023445	0.491188	0.100393	0.010582	0			
FT2	0.054167	-0.00456	-0.03981	0.030426	-0.1491	0.043559	0.336014	0.543231	-0.09098	1			
FT3	-0.11333	0.543231	-0.09425	-0.12283	0.234666	0.086714	0.152574	0.173326	0.025991	1			
MH1	0.023127	-0.11327	0.176568	0.010394	0.01087	-0.21932	0.594228	0.066675	0.283839	1			
MH2	-0.03535	-0.05351	-0.00873	0.127918	0.293746	0.006584	0.602926	-0.09948	0.12394	1			
MH3	0.009644	-0.07673	-0.11808	-0.10402	0.27426	-0.11216	0.619756	0.060978	0.070465	1			
MH4	-0.06385	-0.06604	-0.09454	-0.1593	-0.01658	0.264913	0.318542	-0.06265	0.516865	1			
MH5	0.004792	-0.02061	-0.04036	-0.07289	-0.06482	-0.00106	-0.07746	0.000941	0.917103	1			

8.4.5 SEM Results

```
lavaan 0.6.16 ended normally after 529 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                       147

  Number of observations                           208

Model Test User Model:

  Test statistic                               598.836
  Degrees of freedom                               448
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              3609.471
  Degrees of freedom                               561
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.951
  Tucker-Lewis Index (TLI)                       0.938

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)               2687.664
  Loglikelihood unrestricted model (H1)       2987.082

  Akaike (AIC)                               -5081.328
  Bayesian (BIC)                             -4590.710
  Sample-size adjusted Bayesian (SABIC)      -5056.477

Root Mean Square Error of Approximation:

  RMSEA                                          0.040
  90 Percent confidence interval - lower         0.031
  90 Percent confidence interval - upper         0.048
  P-value H_0: RMSEA <= 0.050                    0.976
  P-value H_0: RMSEA >= 0.080                    0.000

Standardized Root Mean Square Residual:

  SRMR                                           0.053

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PE =~
    PE1               1.000                               0.168    0.836
    PE2               1.029    0.065   15.731    0.000    0.173    0.834
    PE3               1.045    0.090   11.580    0.000    0.176    0.763
    PE4               1.005    0.082   12.272    0.000    0.169    0.807
  EE =~
    EE1               1.000                               0.127    0.782
    EE2               1.108    0.090   12.352    0.000    0.141    0.851
```

```
    EE3               0.945    0.083   11.356    0.000    0.120    0.778
    FT3               0.502    0.077    6.512    0.000    0.064    0.468
  PV =~
    PV1               1.000                               0.182    0.805
    PV2               1.201    0.077   15.584    0.000    0.219    0.953
    PV3               1.040    0.080   13.031    0.000    0.190    0.796
  PF =~
    PF1               1.000                               0.266    0.921
    PF2               0.662    0.085    7.822    0.000    0.176    0.661
    PF3               0.551    0.077    7.170    0.000    0.147    0.629
  SM =~
    SM1               1.000                               0.163    0.844
    SM2               1.030    0.103   10.039    0.000    0.167    0.874
  SL =~
    SL1               1.000                               0.209    0.937
    SL2               0.936    0.085   11.024    0.000    0.195    0.837
  PG =~
    PG1               1.000                               0.095    0.826
    PG2               1.391    0.115   12.092    0.000    0.132    0.792
    PG3               1.123    0.107   10.495    0.000    0.106    0.712
    MH1               1.242    0.115   10.830    0.000    0.118    0.699
    MH2               1.040    0.101   10.321    0.000    0.098    0.673
    MH3               0.975    0.092   10.554    0.000    0.092    0.715
  VM =~
    VM1               1.000                               0.146    0.684
    VM2               0.807    0.117    6.896    0.000    0.118    0.631
    VM3               0.768    0.145    5.304    0.000    0.112    0.451
    FT2               0.698    0.118    5.897    0.000    0.102    0.512
  PR1 =~
    Spotify.Free      1.000                               0.210    0.649
    YouTube.Free      0.687    0.123    5.602    0.000    0.144    0.493
  PR2 =~
    Amazon.Music      1.000                               0.211    1.000
  PR3 =~
    Spotify.Premim    1.000                               0.353    1.000
  PR4 =~
    Apple.Music       1.000                               0.211    1.000
  PR5 =~
    YouTube.Premim    1.000                               0.294    1.000

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  PR1 ~
    PE               -0.237    0.136   -1.745    0.081   -0.190   -0.190
    EE               -0.008    0.200   -0.041    0.968   -0.005   -0.005
    PV               -0.326    0.140   -2.330    0.020   -0.283   -0.283
    PF                0.363    0.096    3.775    0.000    0.460    0.460
    SI                0.064    0.142    0.450    0.653    0.049    0.049
    SL                0.050    0.107    0.468    0.640    0.050    0.050
    PG                0.446    0.283    1.575    0.115    0.201    0.201
    VM                0.429    0.210    2.040    0.041    0.298    0.298
  PR2 ~
    PE                0.131    0.111    1.183    0.094    0.104    0.104
    EE                0.392    0.165    2.369    0.018    0.236    0.236
    PV               -0.076    0.110   -0.691    0.489   -0.066   -0.066
    PF                0.071    0.067    1.051    0.293    0.089    0.089
    SI               -0.209    0.117   -1.787    0.074   -0.161   -0.161
    SL                0.128    0.088    1.442    0.149    0.126    0.126
    PG                0.214    0.231    0.927    0.354    0.096    0.096
    VM               -0.410    0.173   -2.372    0.018   -0.285   -0.285
  PR3 ~
    PE                0.465    0.152    3.059    0.002    0.222    0.222
    EE                0.796    0.227    3.505    0.000    0.286    0.286
    PV                0.426    0.154    2.759    0.006    0.220    0.220
```

```
    PF                -0.360    0.102   -3.526    0.000   -0.271   -0.271
    SI                 0.001    0.158    0.008    0.993    0.001    0.001
    SL                -0.021    0.119   -0.179    0.858   -0.013   -0.013
    PG                -0.303    0.313   -0.969    0.333   -0.081   -0.081
    VM                -0.222    0.228   -0.971    0.331   -0.092   -0.092
  PR4 ~
    PE                 0.262    0.105    2.493    0.013    0.208    0.208
    EE                -0.780    0.161   -4.845    0.000   -0.470   -0.470
    PV                -0.082    0.103   -0.794    0.427   -0.071   -0.071
    PF                -0.033    0.063   -0.527    0.598   -0.042   -0.042
    SI                 0.436    0.112    3.885    0.000    0.336    0.336
    SL                -0.338    0.087   -3.897    0.000   -0.334   -0.334
    PG                 0.146    0.217    0.674    0.500    0.066    0.066
    VM                 0.453    0.165    2.748    0.006    0.314    0.314
  PR5 ~
    PE                -0.508    0.141   -3.602    0.000   -0.290   -0.290
    EE                 0.139    0.205    0.676    0.499    0.060    0.060
    PV                 0.537    0.143    3.764    0.000    0.333    0.333
    PF                -0.284    0.091   -3.107    0.002   -0.257   -0.257
    SI                 0.062    0.145    0.428    0.668    0.034    0.034
    SL                 0.158    0.111    1.430    0.153    0.112    0.112
    PG                -0.088    0.288   -0.306    0.760   -0.028   -0.028
    VM                 0.125    0.209    0.595    0.552    0.062    0.062

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
 .PG2 ~~
   .PG3                0.004    0.001    3.232    0.001    0.004    0.329
 .PE1 ~~
   .PE2                0.003    0.002    1.720    0.085    0.003    0.227
 .PF1 ~~
   .PF3               -0.014    0.005   -3.097    0.002   -0.014   -0.691
 .PG3 ~~
   .MH3               -0.002    0.001   -2.322    0.020   -0.002   -0.201
 .PG2 ~~
   .MH3               -0.002    0.001   -2.363    0.018   -0.002   -0.219
  PE ~~
    EE                 0.010    0.002    4.974    0.000    0.456    0.456
    PV                 0.012    0.003    4.483    0.000    0.383    0.383
    PF                -0.006    0.003   -1.635    0.102   -0.126   -0.126
    SM                 0.007    0.002    2.880    0.004    0.241    0.241
    SL                 0.010    0.003    3.648    0.000    0.299    0.299
    PG                 0.005    0.001    3.716    0.000    0.312    0.312
    VM                 0.007    0.002    2.826    0.005    0.267    0.267
  EE ~~
    PV                 0.009    0.002    4.272    0.000    0.369    0.369
    PF                -0.002    0.003   -0.673    0.501   -0.052   -0.052
    SM                 0.008    0.002    4.082    0.000    0.366    0.366
    SL                 0.009    0.002    4.035    0.000    0.341    0.341
    PG                 0.006    0.001    5.090    0.000    0.468    0.468
    VM                 0.007    0.002    3.854    0.000    0.389    0.389
  PV ~~
    PF                -0.023    0.004   -5.425    0.000   -0.464   -0.464
    SM                 0.011    0.003    4.193    0.000    0.363    0.363
    SL                 0.008    0.003    2.816    0.005    0.220    0.220
    PG                 0.005    0.001    3.682    0.000    0.301    0.301
    VM                 0.004    0.002    1.891    0.059    0.168    0.168
  PF ~~
    SM                -0.004    0.003   -1.301    0.193   -0.101   -0.101
    SL                 0.004    0.004    0.932    0.352    0.070    0.070
    PG                -0.002    0.002   -1.125    0.261   -0.085   -0.085
    VM                 0.005    0.003    1.394    0.163    0.122    0.122
  SM ~~
    SL                 0.013    0.003    4.521    0.000    0.393    0.393
```

```
    PG                0.005    0.001    3.991    0.000    0.347    0.347
    VM                0.005    0.002    2.331    0.020    0.220    0.220
  SL ~~
    PG                0.006    0.002    3.681    0.000    0.300    0.300
    VM                0.012    0.003    3.906    0.000    0.376    0.376
  PG ~~
    VM                0.008    0.001    5.087    0.000    0.548    0.548
 .PR1 ~~
   .PR2               0.005    0.004    1.326    0.185    0.183    0.183
   .PR3               0.005    0.005    1.065    0.287    0.148    0.148
   .PR4              -0.003    0.003   -0.908    0.364   -0.131   -0.131
   .PR5              -0.017    0.005   -3.685    0.000   -0.532   -0.532
 .PR2 ~~
   .PR3              -0.008    0.004   -1.914    0.056   -0.142   -0.142
   .PR4               0.006    0.003    2.289    0.022    0.178    0.178
   .PR5              -0.004    0.004   -1.021    0.307   -0.075   -0.075
 .PR3 ~~
   .PR4              -0.008    0.004   -2.121    0.034   -0.167   -0.167
   .PR5              -0.009    0.005   -1.874    0.061   -0.138   -0.138
 .PR4 ~~
   .PR5               0.001    0.003    0.228    0.820    0.017    0.017

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .PE1               0.012    0.002    6.152    0.000    0.012    0.301
   .PE2               0.013    0.002    6.191    0.000    0.013    0.304
   .PE3               0.022    0.003    8.166    0.000    0.022    0.417
   .PE4               0.015    0.002    7.360    0.000    0.015    0.349
   .EE1               0.010    0.001    7.788    0.000    0.010    0.388
   .EE2               0.008    0.001    6.210    0.000    0.008    0.276
   .EE3               0.009    0.001    7.860    0.000    0.009    0.395
   .FT3               0.014    0.001    9.789    0.000    0.014    0.781
   .PV1               0.018    0.002    8.396    0.000    0.018    0.353
   .PV2               0.005    0.002    2.860    0.004    0.005    0.092
   .PV3               0.021    0.002    8.522    0.000    0.021    0.366
   .PF1               0.013    0.007    1.695    0.090    0.013    0.152
   .PF2               0.040    0.005    8.108    0.000    0.040    0.563
   .PF3               0.033    0.005    6.798    0.000    0.033    0.604
   .SM1               0.011    0.002    4.334    0.000    0.011    0.287
   .SM2               0.009    0.003    3.462    0.001    0.009    0.237
   .SL1               0.006    0.003    1.809    0.070    0.006    0.123
   .SL2               0.016    0.003    4.910    0.000    0.016    0.299
   .PG1               0.004    0.001    7.323    0.000    0.004    0.318
   .PG2               0.010    0.001    7.293    0.000    0.010    0.372
   .PG3               0.011    0.001    8.243    0.000    0.011    0.494
   .MH1               0.014    0.002    9.019    0.000    0.014    0.512
   .MH2               0.012    0.001    9.184    0.000    0.012    0.547
   .MH3               0.008    0.001    8.214    0.000    0.008    0.489
   .VM1               0.024    0.003    7.126    0.000    0.024    0.532
   .VM2               0.021    0.003    7.911    0.000    0.021    0.602
   .VM3               0.049    0.005    9.334    0.000    0.049    0.796
   .FT2               0.029    0.003    8.993    0.000    0.029    0.738
   .Spotify.Free      0.061    0.010    6.199    0.000    0.061    0.578
   .YouTube.Free      0.065    0.007    8.841    0.000    0.065    0.757
   .Amazon.Music      0.000                               0.000    0.000
   .Spotify.Premim    0.000                               0.000    0.000
   .Apple.Music       0.000                               0.000    0.000
   .YouTube.Premim    0.000                               0.000    0.000
    PE                0.028    0.004    6.900    0.000    1.000    1.000
    EE                0.016    0.003    6.379    0.000    1.000    1.000
    PV                0.033    0.005    6.828    0.000    1.000    1.000
    PF                0.071    0.011    6.473    0.000    1.000    1.000
    SM                0.026    0.004    6.393    0.000    1.000    1.000
    SL                0.044    0.006    7.433    0.000    1.000    1.000
```

```
    PG                 0.009    0.001    6.979    0.000    1.000    1.000
    VM                 0.021    0.005    4.741    0.000    1.000    1.000
   .PR1                0.017    0.008    2.011    0.044    0.384    0.384
   .PR2                0.039    0.004    9.579    0.000    0.884    0.884
   .PR3                0.073    0.008    9.595    0.000    0.586    0.586
   .PR4                0.031    0.004    8.679    0.000    0.708    0.708
   .PR5                0.063    0.006    9.785    0.000    0.728    0.728

R-Square:
                   Estimate
    PE1                0.699
    PE2                0.696
    PE3                0.583
    PE4                0.651
    EE1                0.612
    EE2                0.724
    EE3                0.605
    FT3                0.219
    PV1                0.647
    PV2                0.908
    PV3                0.634
    PF1                0.848
    PF2                0.437
    PF3                0.396
    SM1                0.713
    SM2                0.763
    SL1                0.877
    SL2                0.701
    PG1                0.682
    PG2                0.628
    PG3                0.506
    MH1                0.488
    MH2                0.453
    MH3                0.511
    VM1                0.468
    VM2                0.398
    VM3                0.204
    FT2                0.262
    Spotify.Free       0.422
    YouTube.Free       0.243
    Amazon.Music       1.000
    Spotify.Premim     1.000
    Apple.Music        1.000
    YouTube.Premim     1.000
    PR1                0.616
    PR2                0.116
    PR3                0.414
    PR4                0.292
    PR5                0.272


>
```