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Music Streaming Services: Understanding the drivers of customer purchase and intention to recommend these services

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Dissertation report presented as partial requirement for obtaining the Master's degree in Statistics and Information Management

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MUSIC STREAMING SERVICES: UNDERSTANDING THE DRIVERS OF CUSTOMER PURCHASE AND INTENTION TO RECOMMEND THESE SERVICES

by

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Dissertation report presented as partial requirement for obtaining the Master's degree in Statistics and Information Management, with a specialization in Information Analysis and Management

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Aos meus pais.

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ABSTRACT

The music industry has undergone strong changes in relation to its production, distribution and consumption habits, due to the exponential development of new technologies, namely streaming platforms. The fact that sales from physical copies continue to decline significantly made it mandatory for this industry to reinvent itself by introducing music streaming services as a key part of the development of its business. This study aims to understand the factors that influence the consumption of music through streaming platforms studying, particularly, the intention to purchase a paid version of a music streaming service and to recommend it. Therefore, an extension of the UTAUT2 model (version of the Unified Theory of Acceptance and Use of Technology, applied to the consumer side) was created. An online survey was used to collect data from 324 music streaming services users and the framework was tested using structural equation modelling (SEM). It also included in-depth semi-structured interviews in order to draw conclusions about the profile of the new music consumer. Our findings verify that habit, performance expectancy and price value play the most important role in influencing the intention to use a paid music streaming service. The intention to recommend these services was also confirmed. With this analysis, centred in UTAUT2 theory, we contribute with new insights about music streaming services consumer behaviour, providing several theoretical and practical implications to music streaming services providers.

KEYWORDS

Music streaming services, Music industry, Adoption models, UTAUT2, Premium.

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1. INTRODUCTION

Since the beginning of the oldest societies, music has had a fundamental role in the life of human beings, being undeniably a form of universal expression that unites culturally and emotionally old and future generations (Larsen, Lawson, & Todd, 2009, 2010; Naveed, Watanabe, & Neittaanmäki, 2017). The importance of music in our society has led to the creation of an industry that includes all the concepts inherent to this thematic, such as its organization, distribution and profitability. This industry, made up mostly of countless record labels, has lived golden times through sales of physical copies, thus monopolizing the production and consumption of music. However, from 2001 onwards, it began to suffer the impact of the appearance of new technologies, thus initiating a digital age where the consumer has a greater capacity for decision (Arditi, 2014).

In the light of this event, the space has become limited for this industry as we knew it, and a reinvention of it was mandatory (Warr & Goode, 2011). The decrease in the volume of revenues, mainly due to the lower number of sales of physical copies (Sinclair & Tinson, 2017), led the main record labels to modernize. In particular, the growth of streaming services has revolutionized the process of consuming music, as the number of users of these services keeps increasing (IFPI, 2020). It is known that since 2010, the number of users worldwide, from the Spotify streaming platform, has increased from 15 to 100 million (Aguiar & Waldfogel, 2018).

These platforms are based on a relatively recent business model (Sinclair & Tinson, 2017), that basically consists of the service proposal according two modalities: adoption of an account exempt from monthly costs but in return, there is advertising and other type of restrictions (freemium model), or, on the contrary, the user pays a monthly fee and takes full advantage of the service (premium model) (Anderson, 2009; Doerr, Benlian, Vetter, & Hess, 2010; Hamari, Hanner, & Koivisto, 2017; Sinclair & Tinson, 2017; Wagner, Benlian, & Hess, 2014), with this modality contributing to a substantial increase in the profits of this industry (Arditi, 2018; Wlömert & Papies, 2016).

The aim of freemium is to attract the largest possible number of users (Chen, Leon, & Nakayama, 2018a, 2018b; Kumar, 2014), increasing the probability of many to upgrade to a premium account (Anderson, 2009; Dinsmore, Swani, & Dugan, 2017; Wagner & Hess, 2013), where there are several advantages like no advertising, better sound quality and the possibility of offline access (Dörr, Wagner, Hess, & Benlian, 2013; Wagner et al., 2014). However, it stills unclear how is the process of choose between accounts done, thus, it is important for music streaming companies understanding the motivations of consumers in order to convert free users into paid subscribers (Chen et al., 2018b).

Analysing data from music streaming services revenues, it becomes impossible to ignore its current value. According to statistics obtained on the official website of the International Federation of the Phonography (IFPI), it is observed that in 2019, 56.1% of the profits of this industry were obtained through streaming services. It is visible that this new method of listening to music has radically changed the paradigm of this industry (Tschmuck, 2012; Wlömert & Papies, 2016).

In 2019, the use of these services through a paid subscription has consistently increased, around 33.5%, compared to 2018, with the tendency for this value to continue to rise (IFPI, 2020). Continuing to analyse data from the same source, it is known that revenue from the sale of physical copies decreased by 5.3%, with digital music downloads following the same downward behaviour: around minus 15.3%, in the year 2019, throughout world (IFPI, 2020). In 2019, revenues from streaming for this industry grew by 22.9%, due to an increase in revenues by 24.1% from Premium streaming accounts (IFPI, 2020). Through these facts, it is assumed that streaming can be considered the preferred way of listening to music, mainly due to the mass use of smartphones with internet access in most places (Kim, Nam, & Ryu, 2017) and by not needing to own the music file (Dörr et al., 2013).

One issue about music digitalization is that it has given rise to a high wave of file piracy, with the authors being the biggest victims. It is estimated that the number of illegal downloads is still high, and therefore, taking into account the increasing popularity of streaming services, it is imperative to investing in this type of research, in order to better understand the streaming relation towards music piracy (Borja, Dieringer, & Daw, 2015; Sinclair & Green, 2016). It is said that the use of legal platforms for these services may appeal to an end to music piracy (Wlömert & Papies, 2016).

Given the importance of music in all cultures and considering the millions of users of music streaming services, due to their rapid diffusion and the importance that has been attributed to their use, it is imperative to know more about this digital phenomenon and which factors influence their use (Molteni & Ordanini, 2003; Wang, Yeh, & Liao, 2013). These new consumer practices are recent, which implies that the level of information surrounding this topic is not yet sufficiently abundant and systematic (Sinclair & Green, 2016). There is little research on the willingness to pay for services when the free version is available (Chen et al., 2018a; Dörr et al., 2013), as well as the new freemium model (Doerr et al., 2010; Oestreicher-singer & Zalmanson, 2013; Wagner et al., 2014). Based on the fact that streaming services have made it possible to bridge the gap between the “old age of music” and the digital revolution it has been submitted, the aim of this study is to know the generic patterns of use of these services by consumers, particularly, to understand the consumer decision process when subscribing to a paid account on a music streaming service and to recommend it. This way, the industry can create value for its consumers and ensure adequate levels of profitability (Chen et al., 2018b; Vock, Dolen, & Ruyter, 2013; Wang, Zhang, Ye, & Nguyen, 2005; Wang et al., 2013). Based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), a research model was tested, using data collected from 324 music streaming services users.

The remainder of this study is structured as follows. First, we provide the conceptual background through a deeper analysis of music streaming services and adoption models of technology. This is followed by the research model and hypotheses development. Next, we provide the research methodology, data analysis and discussion of results. Then, we present some practical and theoretical implications and limitations. We conclude with some directions for future work.

2. THEORETICAL BACKGROUND

2.1. MUSIC STREAMING SERVICES

The way we listen to music has changed a lot in the last few years. Lately, new concepts of digital music distribution have been establish, e.g. Music as a Service (MaaS) (Doerr et al., 2010), in which the content is not transferred and therefore differentiating itself from the well-known download, thus promoting access full time instead of physical property (Sinclair & Tinson, 2017). From the physical format to the digital era, the increase and ease of access to the internet was fundamental for all these changes to be possible, namely the appearance of legal streaming platforms (Hamari, Sjöklint, & Ukkonen, 2016; Sinclair & Tinson, 2017). One factor that contributed to this phenomenon of information and content expansion (in this specific case, musical), is the constant use of technology, through smartphones (Johansson, Werner, Åker, & Goldenzwaig, 2019).

A music streaming service offers several functions to its users, being the main focus of the supply of extensive libraries of songs and albums, from the internet connection (Zimmer, 2018). Nowadays, these services are the fastest growing music option (Cesareo & Pastore, 2014). There are two types of users of streaming services: those who subscribe to an account exempt from usufruct fees and financed by advertising and those who sign an account, paying a monthly fee, which offers several features (Thomes, 2013). Thomes (2013) revealed that listening to music on streaming services, free of charge with advertising, may not cause loss of revenues, actually, it could help in the fight against piracy. These services make profits by combining a financial model through advertising, called freemium, and another type of account with access to other kind of functionalities, in which the user pays a monthly fee, the premium model (Doerr et al., 2010), which should stand out for its more advantageous features and functions, compared to the free version of it (Ye, Zhang, Nguyen, & Chiu, 2004). Currently, the most popular music streaming service in the world is Spotify, founded in Stockholm, 2006. The avid growth of this platform demonstrates its economic and cultural importance, influencing today's society (Vonderau, 2017). According to data from the first quarter of 2020, the number of Premium users of this platform was 130 million, 39% European, 29% North American, 21% Latin American and 11% from the rest of the world (Spotify, 2020). From the same source, it is known that for the same period, profits of about 1.700 million euros were reported from premium services, with revenues growing by 23%, while revenues from ad-supported services increased by 17% (fell short as expectations as a result of the impact of the COVID-19 pandemic) (Spotify, 2020). It is also important to mention the exponential growth of podcast demand (audio or video files, available on streaming platforms): in April 2020, 19% of users of the Spotify platform, interacted with the option of listening to podcasts, with an increase compared to last year (Spotify, 2020). By the end of 2020, Spotify expected to have between 143 to 153 million Premium users, according to the same report. To achieve this growth, the ad-supported services were key, granting the users free access to content (Vonderau, 2017). Still, without being able to convert them into paid subscribers, there will not be any profitability (Chen et al., 2018a).

The digital revolution experienced in the last decades has brought many advantages to this industry, however it has made piracy easy (Myrthianos, Vendrell-Herrero, Bustinza, & Parry, 2016). Thus, nothing more important for this industry, such as analysing and interpreting consumer behaviour, in order to understand the role of music streaming services in the face of illegal music downloads (Sinclair & Green, 2016).

2.2. ADOPTION MODELS

Understanding what consumers value and their consumption patterns is vital for the effective growth of any service. Due to the digitalization process that the music industry has been under, the need to understand better the process of adopting online music streaming services, namely which factors weigh in the decision to purchase a Premium model, has become primordial (Chen et al., 2018b). Music streaming services are considered Information Systems (IS), where the first theories about the adoption of technology were applied. One issue about IS is the difficulty in identifying factors that lead people to accept and use systems developed and implemented by others. However, over the past few decades, several theories and approaches have been developed to solve this problem (King & He, 2006). The basic concept of technology adoption can be described as the combination of individual reactions, intentions to use and actual use (Venkatesh, Morris, Davis, & Davis, 2003).

One of the most fundamental adoption theories is Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), being used as a basis for many other adoption theories about consumer behaviour. TRA states that individual behaviour results from the behavioural intention to perform and attitude, always taking into account the social norms that involve the intention (Fishbein & Ajzen, 1975). Cesareo & Pastore (2014) used TRA to measure consumers' willingness to try a subscription based music streaming service, where variables such as "importance and exposure to music", "involvement and interest" and "attitude towards online piracy" were used. "Economic benefits", "hedonic benefits" and "moral judgment" were used in order to explain the "attitude towards online piracy" as well.

The Theory of Planned Behaviour (TPB) (Ajzen, 1991) is an extension of the previous TRA, as it adds a new component: the perceived behavioural control, improving the predictive power in comparison with the TRA (Ajzen, 1991). This exogenous variable has a direct effect on the subject's intention and final behaviour (Madden, Ellen, & Ajzen, 1992). This theory or extensions of it have been used in several studies within music streaming services adoption context (Cronan & Al-Rafee, 2008; Dörr et al., 2013; Kwong & Park, 2008; Lin, Hsu, & Chen, 2013; Peace, Galletta, & Thong, 2003; Plowman & Goode, 2009; Wagner & Hess, 2013; Yoon, 2011). Yoon (2011) combined the TPB and ethics theory, in order to study digital piracy. Peace et al. (2003) studied software piracy with TPB as a framework, adding variables such as "severity of punishment'', "cost of software" and "certainty of punishment". This study can also be applied in the context of music piracy. Cronan & Al-Rafee (2008) focused on understanding digital piracy using the TPB as a basis to determine factors that influence piracy, adding variables such as "past piracy behaviour" and "moral judgment". Plowman & Goode (2009) presented some factors that affect the intention to illegally download, using an extended version of the TPB. Dörr et al. (2013) used the TPB as a structure to explain the intention of a consumer to pay for a music streaming service. The following variables were added as extensions to the model: "submission of music recommendations", "search for music recommendations", "desire to own", "flat rate preference" and "relative advantage of MaaS" (e.g. sound quality). Wagner & Hess (2013) analysed the consumer's motivations to subscribe to a paid music streaming service, with a free version of the same service available. TPB was used with extensions like "preference for tangibility and innovativeness". As an outcome, the free account had a negative impact on the user's intention to pay for a premium version. It was verified that music streaming services should focus on the premium version and have to set a time limit for the free subscription (Wagner & Hess, 2013).

The Technology Acceptance Model (TAM) (Davis, 1989), is one of the most important model in the context of technology adoption and use (Cheong & Park, 2005). Based on TRA, it uses two new factors - perceived usefulness and perceived ease of use - which are well accepted regarding the intention to use technology (King & He, 2006). Some derivations of this model have also been proposed (Venkatesh & Bala, 2008; Wang, 2008), like TAM2, where attitude is dropped out due to its role as a mediator between intention and both perceived usefulness and perceived ease of use was not very relevant (Davis, Bagozzi, & Warshaw, 1989; Lee & Lehto, 2013; Venkatesh & Davis, 2000). Kwong & Park (2008) applied TPB and TAM's attitude in a digital music services study where subjective norm had a significant effect on the consumer's intention to subscribe (Kwong & Park, 2008).

In 2003, Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), based on eight prominent theories: TRA (Theory of Reasoned Action), TPB (Theory of Planned Behaviour), TAM (Technology Acceptance Model), MM (Motivation Model), C-TAM-TPB (combined TAM and TPB), MPCU (Model of PC Utilization), DIT (Diffusion of Innovation Theory), SCT (Social Cognitive Theory). Consisting of four constructs: performance expectancy, effort expectancy, social influence and facilitating conditions, the UTAUT obtained satisfactory results, creating a model that explains about 70 percent of the variance in behavioural intention to use a technology and about 50 percent of the variance in technology use (Venkatesh et al., 2003; Venkatesh, Thong, & Xu, 2012).

This study intends to use this theory, more specifically, an extension (UTAUT2), as a basis to create the explanatory model in our context of music streaming services. In the following section, we will describe UTAUT2 and its relevance.

2.2.1 Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

The original UTAUT consists of four constructs: performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh et al., 2003). After its release, the model was tested in different contexts and in 2012, it was extended to the consumer context, developing the UTAUT2 (Venkatesh et al., 2012). UTAUT2 is an extension of the original model, adding three new constructs: hedonic motivation, price value and habit. Age, gender and experience were considered moderators of behavioural intention and technology use (Venkatesh et al., 2012). According to Venkatesh et al. (2012), the changes significantly improved this model because the variance explained in behavioural intention increased from 56 to 74 percent and in technology use it increased from 40 to 52 percent.

This theory was chosen mainly due to its ability to adapt to various technologies and because it is oriented to the consumer's perspective. Venkatesh et al. (2012) claimed that for future research, in order to the theory development (UTAUT2), it could be tested in different countries, in groups of different ages and in different technologies. Therefore, this study aims to apply the UTAUT2 to the music streaming services panorama and to identify relevant factors that can be useful in the applicability of UTAUT2 in that context.

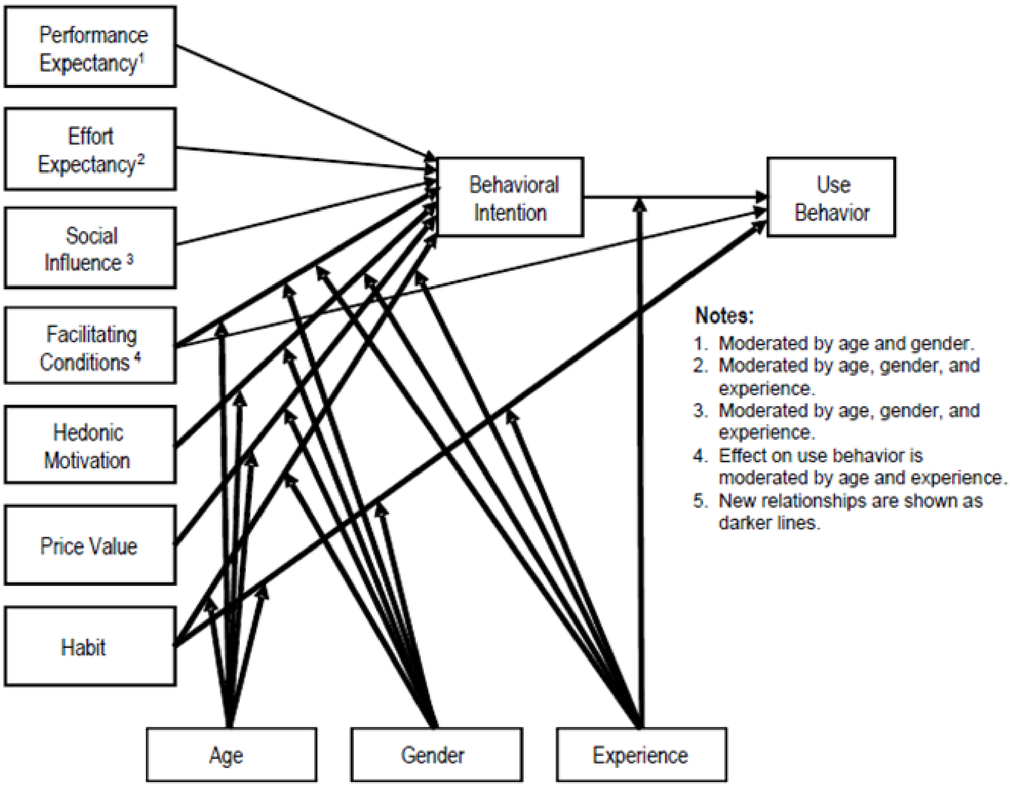

Figure 1 – UTAUT2 model

3. RESEARCH MODEL AND HYPOTHESES

The model tested in this study is an extension of the theoretical UTAUT2 model. Extra variables were added in order to analyse the behavioural intention to purchase a paid version of a music streaming service and to recommend it. Those variables were found in the literature review and in the semi-structured interviews, previously conducted. Then, the conceptual model is shown on Fig.2.

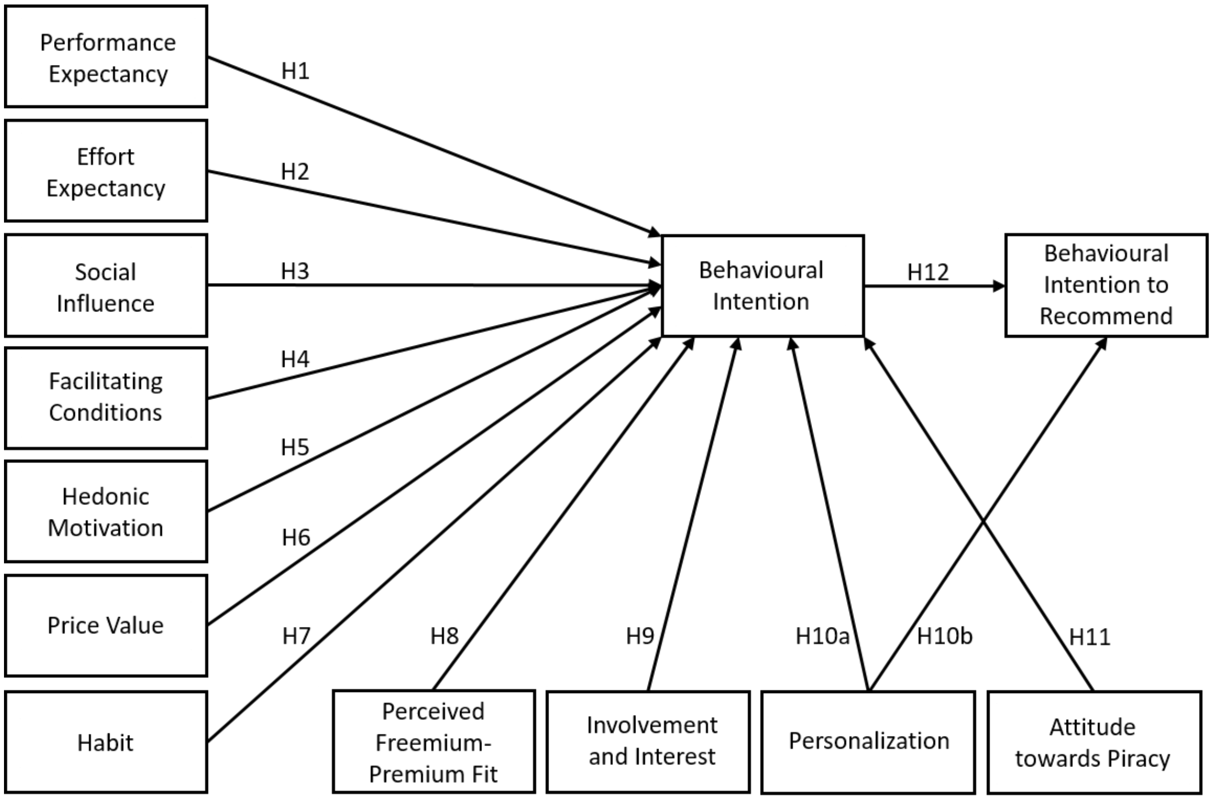

Figure 2 – Research model

In the following section, the hypotheses that constitute the conceptual model will be presented and developed, as well as the theoretical research that supports and justifies them.

3.1. UTAUT2 VARIABLES

Performance expectancy

Performance expectancy is defined as the degree to which using a technology will provide benefits to consumers in performing certain activities (Venkatesh et al., 2012). According to Chu & Lu (2007), perceived usefulness (variable from TAM, functioning as a root-construct in performance expectancy - Venkatesh et al., 2003) is defined as the degree to which the consumer thinks that listening to music online would fulfil a certain purpose (Chu & Lu, 2007). Although online music services aim to deliver an entertaining experience, they also provide functional benefits to people (Chu & Lu, 2007). Hampton-Sosa (2019) said that perceived usefulness and perceived enjoyment leads to the purchase of a music streaming service (Hampton-Sosa, 2019). Some attributes from the utilitarian character of the music streaming services are tools to find music, organize titles, sort through rankings and commentary, access product information and facilitate music sharing (Hampton-Sosa, 2017). The construct performance expectancy has been known as the most effective factor for explaining adoption intention (Baptista & Oliveira, 2015; Luo, Li, Zhang, & Shim, 2010). Hence, we formulate the following hypothesis:

H1. Performance expectancy (PE) is positively related to behavioural intention (BI).

Effort expectancy

Effort expectancy is defined as the degree of ease associated with consumers' use of technology (Venkatesh et al., 2012). According to Kwong & Park (2008), perceived ease of use (variable from TAM, functioning as a root-construct in performance expectancy - Venkatesh et al., 2003) is a significant predictor of intention (Kwong & Park, 2008). The same authors stated that the access to online music should be effortless and that the service quality creates a belief in the users that the service is easier to use (Kwong & Park, 2008). Davis (1989) claimed that if an IS is considered easy to use by users, the probability of being accepted and adopted by the community will be greater (Davis, 1989). In the in-depth semi-structured interviews previously carried out, most of the participants affirmed that the ease of access was decisive in the use of music streaming services. Effort expectancy was considered an important variable in estimating intention to use IS (van der Heijden, 2004; Venkatesh et al., 2012), thus, the following hypothesis is formulated:

H2. Effort expectancy (EE) is positively related to behavioural intention (BI).

Social influence

Social influence is defined as the extent to which consumers perceive that important others (e.g. family and friends) believe they should use a particular technology (Venkatesh et al., 2012). Social influence was based on the subjective norm construct, present in other adoption theories and its function is to measure the social pressure applied to the individual, which leads him to perform (or not) a certain behaviour (Ajzen, 1991; Fishbein & Ajzen, 1975). Several studies in the entertainment field proved its relevance (Chen et al., 2018b; Dörr et al., 2013; Kwong & Park, 2008; Molteni & Ordanini, 2003; Yang, 2013). Therefore, we hypothesize:

H3. Social influence (IS) is positively related to behavioural intention (BI).

Facilitating conditions

Facilitating conditions refer to consumers perceptions of the resources and support available to perform a behaviour (Venkatesh et al., 2012). This construct and its roots have been thought to include technological aspects that are designed to remove barriers to use (Venkatesh et al., 2003). A consumer that has access to a favourable set of facilitating conditions is more likely to have a higher intention to use a technology (Venkatesh et al., 2012). Starting from the beginning that music streaming services are internet-based services, it is necessary to go online and have resources to do that (Kwong & Park, 2008). Therefore, we hypothesize:

H4. Facilitating conditions (FC) are positively related to behavioural intention (BI).

Hedonic motivation

Hedonic Motivation is defined as the fun or pleasure derived from using a technology (Venkatesh et al., 2012). In this context, is the degree to which a user expects enjoyment from listening to streamed music (Chen et al., 2018b). Music streaming services can be considered hedonic IS due to the creation of leisure and entertainment for their users, instead of carrying out a practical task (Chen et al., 2018b). Hedonic motivation has been conceptualized as perceived enjoyment (van der Heijden, 2004; Venkatesh et al., 2012) and often considered a reliable predictor of technology adoption (Chen et al., 2018b; van der Heijden, 2004). Hedonic motivation has been one of the most important determinants of acceptance and use (Brown & Venkatesh, 2005; Venkatesh et al., 2012). Consequently, this variable is suggested as a factor that impacts a consumer's intention to purchase these services and therefore, we hypothesize:

H5. Hedonic motivation (HM) is positively related to behavioural intention (BI).

Price value

Price value is defined as consumers' cognitive trade-off between the perceived benefits of the applications and the monetary cost for using them (Dodds, Monroe, & Grewal, 1991; Venkatesh et al., 2012). This construct was included in UTAUT2 due to the monetary costs of the consumer use setting (Venkatesh et al., 2012). Several studies referred price as a key factor of intention (Bhattacharjee, Gopal, & Sanders, 2003; Chiang & Assane, 2009; Doerr et al., 2010; Dörr et al., 2013; Papies, Eggers, & Wlömert, 2011; Sinha & Mandel, 2008; Wagner & Hess, 2013; Weijters & Goedertier, 2016; Ye et al., 2004). In the context of music streaming services, it is known that the paid version coexists in a highly competitive environment due to the existence of free alternatives, thus, makes sense that price value also determines users' intention to purchase the premium version. The price value is favourable when the benefits of using a technology are perceived to be greater than the monetary cost (Venkatesh et al., 2012). Therefore, we hypothesize:

H6. Price value (PV) is positively related to behavioural intention (BI).

Habit

Habit is defined as a perceptual construct that reflects the results of prior experiences (Venkatesh et al., 2012). Past behaviour seems to be determinant to the present behaviour (Ajzen, 2002; Kim & Malhotra, 2005), impacting behavioural intention (Venkatesh, 2000). Habit's influence as a predictor of intention has been analysed in several studies (Kim, Malhotra, & Narasimhan, 2005; Kim & Malhotra, 2005; Limayem, Hirt, & Cheung, 2007; Limayem & Hirt, 2003; Venkatesh et al., 2012). According to Ye et al. (2004), a consumer's willingness to pay for an online service can be related to how habitual the consumer has become to using that service (Ye et al., 2004). Therefore, we hypothesize:

H7. Habit (H) is positively related to behavioural intention (BI).

3.2. Extensions

To better fit the UTAUT2 model in the music streaming services context, we will proceed to adjust it. By combining new variables from other theoretical and modified models, we aim to make it less generic and better defined to its application to the music streaming services purchase and recommendation.

Perceived freemium-premium fit

Regarding the conversion of freemium users to premium users, it is necessary to evaluate the adjustment that exists between both versions. That adjustment (freemium-premium fit, in our case) is considered a measure that defines the similarity between the features of the free and paid version, and the higher the value, the greater the number of premium features contained in the freemium version (Wagner et al., 2014). The same authors claimed that by lowering this value, the freemium version becomes more basic, cutting back on premium features and imposing more restrictions such as a limit on the number of hours of music consumption per month, more advertising or stopping offline access. If the freemium version is already quite complete and rich in premium features, that is, if the premium fit is high, the user will adopt the free version and, thus, will create a positive behaviour towards the same (Hamari, Hanner, & Koivisto, 2020; Wagner et al., 2014). Consumers take this measure into account when purchasing a service with a free version available (d'Astous & Landreville, 2003; Wagner et al., 2014). The free trial period has been considered quite efficient to get the consumer to sign up for the paid version of the service (Cheng & Tang, 2010; Wagner et al., 2014; T. Wang, Oh, Wang, & Yuan, 2013). According to Wlömert & Papies (2016), greater sensitivity to restrictions, means greater propensity to subscribe to a premium account (Wlömert & Papies, 2016). In the in-depth semi-structured interviews previously carried out, some freemium users affirmed that they preferred to deal with ads and other restrictions than to pay for a music streaming service, enhancing the ability of some individuals to adapt to the existence of advertising (Li & Cheng, 2014) and thus, the conversion of many of them to premium accounts does not happen. Weijters et al. (2014) concluded that it is the youngest layers that most use ad-based services, as they tend to be the most tolerant to them and due, mainly, to economic reasons. It should be noted that a product/service free of cost, is easier to recommend (Lee, Kumar, & Gupta, 2013). Therefore, we hypothesize:

H8. A higher perceived freemium-premium fit (PF) is negatively related to behavioural intention (BI).

Involvement and interest

It is known that the more involved and interested a consumer is in a product, the greater the dedication to analyse and evaluating its advantages and/or disadvantages (Bian & Moutinho, 2009; Cesareo & Pastore, 2014). Styvén (2010) states that an individual who is very involved in the music subject, will be more likely to acquire technologies in relation to it, in all formats (Styvén, 2010). Aguiar & Martens (2016) also suggest that consumers with a greater interest in music, assimilate streaming as a means to acquire digital music (Aguiar & Martens, 2016). In a study carried out by Cesareo & Pastore (2014), it was tested whether users most involved and interested in using a music streaming service are most likely to try a subscription-based service (Cesareo & Pastore, 2014). The results were favourable and thus, we hypothesize:

H9. Involvement and interest (II) is positively related to behavioural intention (BI).

Personalization

Personalization is defined as a process that changes the functionality, interface, information access and content or distinctiveness of a system, to increase its personal relevance to an individual or a category of individuals (Blom, 2000; Haiyan & Marshall, 2006). It is a marketing strategy, where consumer information is used to create appropriate solutions for them (Peppers & Rogers, 1997;

Vesanen, 2007). Personalization needs to be adapted to the dynamic user interests (Anand & Mobasher, 2007). The possibility of personalization has a strong impact on the opinion of music streaming services users (Lee & Waterman, 2012), with the creation of automatic playlists based on recommendation algorithms being important for them (Prey, 2018). Some customizable features could be only available in the premium version of these services, in order to highlight the differences between types of accounts (Wagner et al., 2014).

The impact of personalization on behavioural intention to recommend a service has been also argued. It is known that the effect of service personalization on loyalty exists (Ball, Coelho, & Vilares, 2006; Coelho & Henseler, 2012). Since customer loyalty can be manifested by the willingness to recommend a service to friends or acquaintances (Ball et al., 2006), it would be interesting to test whether personalization impacts the behavioural intention to recommend a paid music streaming service, filling a research gap in this context.

Very little research has been done in order to provide effective evidence to show that personalization is useful to consumer satisfaction (Anand & Mobasher, 2007; Liang, Lai, & Ku, 2006), therefore, to obtain more insights about the use of these services, we put forward the following hypotheses:

H10a. Personalization (P) is positively related to behavioural intention (BI).
H10b. Personalization (P) is positively related to behavioural intention to recommend (R).

Attitude towards piracy

Attitude toward a behaviour is defined as the degree to which a person has a favourable or unfavourable evaluation or appraisal of the behaviour in question (Ajzen, 1991). Most research in the behaviour field suggests that attitude is one of the most significant factors influencing behavioural intention (Cronan & Al-Rafee, 2008). Several studies indicate that the emergence of streaming platforms had a negative impact on piracy, as they enable access to the desired content, easily and at low cost, if not free of charge (Aguiar & Waldfogel, 2018). This impact is seen by the music industry with optimism (Sinclair & Green, 2016). However, Borja & Dieringer (2016) stated that, possibly, these two ways of acquiring music, piracy or streaming, will coexist in the near future (Borja & Dieringer, 2016). According to Weijters et al. (2014), consumers tend to prefer ethical and legal options, if possible (Weijters, Goedertier, & Verstreken, 2014). The attitude of individuals towards digital piracy was found to be influenced by perceived benefits, perceived risk, and habit (Yoon, 2011). Cesareo & Pastore (2014) declared that a positive attitude towards piracy, negatively influences the intention to subscribe a paid music streaming service (Cesareo & Pastore, 2014), being the most important variables to explain attitude towards piracy mainly of economical nature (Sinha & Mandel, 2008; Weijters et al., 2014). Borja & Dieringer (2015) concluded that college students commonly think of piracy as an attitude that does not harm artists. However, the same authors stated that most consumers are aware that there is a risk (Borja et al., 2015). Aguiar & Martens (2016) have found evidence of a positive relationship between music streaming platforms and purchases of licensed music (Aguiar & Martens, 2016). Peace et al. (2003) proved that punishment severity and punishment certainty have a direct effect on the individual's attitude toward software piracy (Peace et al., 2003). Therefore, after this review on existing research, we hypothesize:

H11. An unfavourable attitude toward piracy (AP) is positively related to behavioural intention (BI).

Behavioural intention to recommend

Recommendation is recognized as a key post-adoption behaviour (Luo, Chea, & Bui, 2016). Previous research assumed that consumers with a higher intention to adopt a new technology are more probable to become adopters of the technology (Kuo & Yen, 2009; Miltgen, Popovič, & Oliveira, 2013; Oliveira, Thomas, Baptista, & Campos, 2016) and then, to recommend to others (Miltgen et al., 2013; Oliveira et al., 2016). It is important to underline that social media has completely changed the way society communicates and exposes its ideas or businesses (Olanrewaju, Hossain, Whiteside, & Mercieca, 2018; Zheng, Cheung, Lee, & Liang, 2015). A positive recommendation or feedback from a friend seems to influence music purchase decisions (Dewan & Ramaprasad, 2014). It is known that the recommendation effect is under research (Luo et al., 2016), mainly due to the focus on the use behaviour construct (Naranjo-Zolotov, Oliveira, & Casteleyn, 2019). Therefore, we hypothesize:

H12. Behavioural intention (BI) is positively related to behavioural intention to recommend (R).

4. RESEARCH METHODOLOGY

The methodological path for the development of this study was composed by a combination of qualitative and quantitative research designs.

4.1. QUALITATIVE RESEARCH

Concerning qualitative analysis, a literature review was carried out and, in an initial phase, semi-structured in-depth interviews were conducted about music streaming services, music piracy and social media. These were of utmost importance to understand the opinion and perspective of the participants, making possible to retain information about the way users (or non-users) deal with music streaming services, enabling the discovery of new motivations, tastes and characteristics of the interviewees, in an attempt to outline their profile. Twenty participants were interviewed, aged between 18-24 years (thirteen participants), 25-34 (five participants), 35-44 (one participant) and > 50 (one participant). The sample was gender balanced, all members have Portuguese nationality and are living in Lisbon.

As results are concerned, eighteen of the twenty interviewees, were familiar with the concept of music streaming and seventeen of them presented Spotify as the best known music streaming service. Regarding the frequency of use, eight respondents use music streaming services daily and six of these elements pay for a premium version (two elements are inserted in Spotify's family packages). One of these six members stated that his motivation to pay for these services was: *"Above all, it is a way to help artists. Since less CDs are purchased, this is a viable way to support their work"*. The main advantages premium users find are: variety of songs and podcasts available in the service, high quality, information regarding bands/musicians, the price value, the possibility of creating personalized playlists, suggestions of new music from algorithms, offline access, unlimited music skipping, no advertising, easy use, access to friends activity, the possibility of listening without having to download and, last but not least, to contribute for the remuneration of musicians/bands. In the total sample, eight people revealed that they do not feel the need to pay for a music streaming service, claiming that they would rather deal with ads and other restrictions than pay for those services. However, three people who are not paid version subscribers are willing to do so because they believe the benefits are worth it. A member whose account regime is part of Spotify's family service said: *"There are quite a few features that I like, such as Radio. The possibility of obtaining recommendations of new music is fascinating and it works quite well. Offline access is also something that should be valued, although today we are almost constantly connected, except when we travel by plane or in areas with little network coverage. In that case, offline access is undoubtedly an asset. It is also interesting to be able to follow people and playlists that we like"*. Regarding the prices charged, eight elements referred to the prices which are affordable and would be willing to spend up to 10€ to obtain the service, if necessary. Almost all individuals who have claimed this fact are subscribers of a premium account. One member of this group said that: *"A music CD costs 20€, as a rule. I don't think Spotify's values are inadequate. If it was more expensive it wouldn't shock me. Artists do not work for free, it is ungrateful to want to have their work for free"*. In the sample, six elements said that they would be willing to pay up to 5€ and the rest have said that the prices are too high and that they are already used to the free account. Regarding the purchase of music in physical format, most of the sample reported that they buy little or nothing, leading to the conclusion that this way of purchasing music is outdated. One member stated that he only likes to buy to collect, if it is from his favourite band/song. In this sample, the main ways for respondents to listen to music is the streaming service Spotify and YouTube, due to the ease of access. One person mentions Apple Music and two other people say that they prefer the free ripping applications that their phone gives them (iPhone users). As for the favourite way to search for songs, the one chosen by Spotify premium users is, unsurprisingly, Spotify. For the rest, the chosen option was YouTube due to the easy access, speed and acquired habit of using this platform, where you can also see the video clip. A user stated that his decision depends on the device he is currently using: *"YouTube, Spotify, SoundCloud (this a little less) - are there alternatives to these? These are the best known forms. When I'm on the computer, I usually search on YouTube, when I'm away from home, I use Spotify, on my phone. There's everything on YouTube and Spotify is the best music streaming service. As for SoundCloud, I use it more when I want to listen to music projects from friends and on a small scale or to listen to full concerts when they are only on this platform, published by the artist"*.

The number of people who currently practice illegal downloads over the internet has visibly decreased as only five members continue to practice this kind of download. In the sample there are three elements that never have done an illegal download. The rest admitted to have already practiced it a lot, however, stopped doing it because more ethical ways have appeared that allow listening to music for free or because nowadays they have a premium account in a music streaming service. Four elements admitted they still download some songs, rarely. Everyone except two members agreed that these services can completely combat piracy in this industry. Most say that this form of consuming music (illegal downloads) is, unfortunately, culturally accepted, as it is not seen as a crime by many. One member, on this subject, said: *"I think there has been more practice than now. In the first decade of this century it was a recurring practice. Nowadays it is more obsolete"*. The risk of this practice is seen, by the majority, as non-existent and many of the interviewees do not know what the consequences of this act are. Three participants agreed that there is risk, but only on a large scale.

4.2. QUANTITATIVE RESEARCH

After the research process, whose purpose would be the acquisition of data regarding the practices of users of music streaming services, it was found to be quite difficult to obtain, citing Aguiar (2017): ''it is usually hard to access data on music consumption through streaming, sales, and piracy'' (Aguiar, 2017). Thus, it was decided to create a questionnaire to overcome this obstacle and apply it to a representative sample of the target population, although it is never entirely possible (Saunders, Lewis, & Thornhill, 2009). The questionnaire was designed based on the studies by Venkatesh et al. (2003) (UTAUT model) and Venkatesh et al. (2012) (UTAUT2 model). The indicators for each construct were adapted from the previously consulted literature (Appendix A), with 53 indicators distributed in a total of 13 constructs.

The scale chosen to measure responses was the 7-Point Likert Scale, 7 points (1-7) representing: strongly disagree, disagree, partially disagree, do not disagree or agree, partly agree, agree and strongly agree. The questionnaire was launched online, a Portuguese version, on social networks and also, sent by email to the NOVA IMS students. Thus, the sampling process used in this study was non-probabilistic for convenience (Iacobucci & Churchill, 2018). The survey was active for one month (August 21 to September 21, 2020), on Qualtrics platform. Demographic and social questions were included in order to be more sensitive about sample characteristics and to envision some possible research hypotheses, in the future. By not defining limits on age, it was possible to acquire a greater variety of responses.

Data was analysed in order to test the previously formulated hypotheses and thus verify whether this version of the UTAUT2 model fits in the context of music streaming services. 439

anonymous and confidential responses were collected and 324 of these proved to be valid for the propose of this study. After the descriptive analysis of the sample (performed using the statistical software SPSS), it was possible to conclude that regarding gender, the sample was balanced, with a slightly higher number of female respondents (50.9%). Around 77% have a level of education at the 'College' level (77.1%). The majority lies in the age group of 18-34 years (83%) and almost 97% are Portuguese. Detailed descriptive statistics on the respondents' characteristics are shown in Table 1.

Table 1 – Descriptive statistics of respondent's characteristics.

Measurement	**Value**	**Frequency**	**%**
Gender	Female	165	50.9
	Male	157	48.5
	Other	2	0.6
Age	< 18	2	0.6
	18-24	133	41.0
	25-34	136	42.0
	35-44	9	2.8
	45-54	30	9.3
	55-64	14	4.3
	> 65	0	0.0
Education	Basic	1	0.3
	High school	64	19.8
	Bachelor	126	38.9
	Post-grad.	34	10.5
	Master	88	27.1
	Doctorate	2	0.6
	Other	9	2.8
Nationality	Portuguese	313	96.6
	Other	11	3.4

5. DATA ANALISYS AND RESULTS

In this section, we tested the developed hypotheses, in order to verify the extended model of UTAUT in the context of music streaming services. The theoretical research model was estimated using the statistical method structural equation modelling (SEM), which is used to evaluate the validity of theories with empirical data (Ringle, Wende, & Becker, 2015). SEM combines two techniques: covariance-based (as represented by LISREL) and variance-based, which partial least squares (PLS) path modelling is the most prominent representative (Henseler, Ringle, & Sinkovics, 2009). PLS was applied to test our model with SmartPLS 3.0 software (Ringle et al., 2015). This powerful technique was chosen mainly due to its capability of avoiding small sample size problems and as it is recommended in an early stage of theoretical development, to test and validate exploratory models, motivated by prediction and exploration (Henseler et al., 2009).

5.1. MEASUREMENT MODEL

In order to assess the measurement model, reliability and validity were evaluated. Reliability was tested using the composite reliability (measure of internal consistency that takes into account that indicators have different loadings) and Cronbach's alpha (estimator based on the indicator intercorrelations), which generally can be interpreted at the same way (Hair, Hult, Ringle, & Sarstedt, 2014; Henseler et al., 2009). As shown in Table 2, all constructs have greater values than 0.7 or really close (PF) for composite reliability and Cronbach's alpha, satisfying all requirements and thus, admitting constructs reliability. The indicator reliability was evaluated through loading values. If they are higher than 0.7, we should retain them, and should be eliminated if below 0.4 (Churchill, 1979; Hair et al., 2014; Henseler et al., 2009). The items FC4, PF4, P5, P6, AP4, AP5 and AP6 (Appendix A) were dropped due to the low factor loading. We kept AP3 and II3 to prevent the construct from being only represented by two indicators.

Immediately after the reliability analysis, convergent validity is measured. Therefore, average variance extracted (AVE) is used (Fornell & Larcker, 1981), being defined as the mean value of the squared loadings of the indicators associated with the construct (Hair et al., 2014). AVE values should be at least 0.5 to indicate sufficient convergent validity and thus, the construct could explain more than half of the variance of its indicators, on average (Hair et al., 2014; Henseler et al., 2009). As seen in Table 2, all constructs present values higher than 0.5.

To assess discriminant validity, Fornell & Larcker (1981) and cross-loadings criteria were used. The Fornell-Larcker criterion (Fornell & Larcker, 1981) allows evaluating discriminant validity on the construct level and the cross-loadings criteria evaluates it on the indicator level (Henseler et al., 2009). According to Henseler et al. (2009) and Hair et al. (2014), the Fornell-Larcker criterion consists on the comparison of the square root of AVE value of each construct with the correlations (of Pearson) between the constructs, being the discriminant validity satisfied when the square roots of AVE are greater than the correlations between constructs. As can be seen in Table 3, this criterion is met (all diagonal values are greater than off-diagonal values). Regarding cross-loadings criterion, the indicators should not have a higher correlation with another construct than with its respective latent variable (Henseler et al., 2009). This criterion is also validated, all the loadings are greater than the correspondent cross-loadings (Appendix B).

The measurement model results assure construct reliability, indicator reliability, convergent validity and discriminant validity of the constructs. Therefore, the constructs can be used to test the structural model, in the next section.

Table 2 – Quality criteria and factor loadings.

Constructs	AVE	Composite reliability	Cronbach's alpha	Item	Loadings	*t*-value
Performance Expectancy (PE)	0.696	0.919	0.891	PE1	0.869	66.860
				PE2	0.743	23.067
				PE3	0.835	40.271
				PE4	0.815	34.223
				PE5	0.902	78.211
Effort Expectancy (EE)	0.778	0.933	0.905	EE1	0.868	28.015
				EE2	0.909	48.059
				EE3	0.925	70.884
				EE4	0.823	24.327
Social Influence (SI)	0.762	0.927	0.895	SI1	0.897	66.171
				SI2	0.916	72.912
				SI3	0.941	105.129
				SI4	0.722	17.327
Facilitating Conditions (FC)	0.705	0.878	0.796	FC1	0.845	39.261
				FC2	0.827	23.202
				FC3	0.847	32.032
Hedonic Motivation (HM)	0.762	0.927	0.896	HM1	0.868	56.340
				HM2	0.819	31.483
				HM3	0.897	58.017
				HM4	0.905	68.642
Price Value (PV)	0.930	0.975	0.962	PV1	0.961	147.674
				PV2	0.967	219.842
				PV3	0.964	213.129
Habit (HT)	0.766	0.929	0.899	HT1	0.889	88.692
				HT2	0.883	54.347
				HT3	0.867	48.854
				HT4	0.862	46.110
Perceived freemium-premium fit (PF)	0.560	0.791	0.670	PF1	0.694	8.611
				PF2	0.695	8.292
				PF3	0.846	17.763
Involvement and Interest (II)	0.756	0.900	0.844	II1	0.968	37.073
				II2	0.968	36.119
				II3	0.628	5.505
Personalization (P)	0.657	0.885	0.827	P1	0.784	24.030
				P2	0.821	28.255
				P3	0.846	39.393
				P4	0.790	26.031
Attitude towards piracy (AP)	0.645	0.842	0.737	AP1	0.881	29.176
				AP2	0.886	35.614
				AP3	0.611	8.103
Behavioural intention (BI)	0.922	0.973	0.958	BI1	0.965	153.218
				BI2	0.957	137.847
				BI3	0.958	134.884

Behavioural int. to recommend (R)	0.952	0.975	0.949	R1	0.976	224.961
				R2	0.975	188.812

Table 3 – Square root of AVE (in bold on diagonal) and factor correlation coefficients.

Const.	PE	EE	SI	FC	HM	PV	HT	PF	II	P	AP	BI	R
PE	**0.834**												
EE	0.423	**0.882**											
SI	0.469	0.236	**0.873**										
FC	0.437	0.612	0.275	**0.840**									
HM	0.619	0.491	0.428	0.434	**0.873**								
PV	0.618	0.337	0.426	0.470	0.537	**0.964**							
HT	0.640	0.347	0.448	0.410	0.496	0.565	**0.875**						
PF	-0.409	-0.184	-0.230	-0.177	-0.315	-0.356	-0.307	**0.749**					
II	0.182	0.169	0.096	0.150	0.122	0.142	0.250	-0.137	**0.870**				
P	0.425	0.389	0.313	0.374	0.365	0.396	0.423	-0.298	0.315	**0.811**			
AP	0.258	0.137	0.257	0.216	0.205	0.344	0.245	-0.121	0.231	0.319	**0.803**		
BI	0.727	0.435	0.444	0.470	0.600	0.691	0.736	-0.433	0.210	0.426	0.357	**0.960**	
R	0.688	0.386	0.503	0.466	0.566	0.669	0.660	-0.401	0.246	0.443	0.335	0.824	**0.976**

Note: **PE** - performance expectancy; **EE** - effort expectancy; **SI** - social influence; **FC** - facilitating conditions; **HM** - hedonic motivation; **PV** - price value; **HT** - habit; **PF** - perceived freemium-premium fit; **II** - involvement and interest; **P** - personalization; **AP** - attitude towards piracy; **BI** - behavioural intention; **R** - behavioural intention to recommend

5.2. STRUCTURAL MODEL

Once we have assumed that the construct measures are reliable and valid, the next step is the assessment of the structural results (Hair et al., 2014). It was verified that there were no collinearity issues. As we do not have any formative constructs, we evaluated the inner variance inflation factor (VIF) and all variables presented values less of 2 or very close, which means that it is acceptable to proceed. The path significance levels were estimated using the bootstrapping technique, which provides an estimate of the shape, spread, and bias of the sampling distribution, treating the observed sample as if it represents the population as creating 5,000 (in this specific case) bootstrap samples (Henseler et al., 2009). The results are shown in Fig. 3.

According to Hair et al. (2014), coefficients of determination (R^2 values) of 0.75, 0.50 and 0.25 are considered as substantial, moderate or weak, respectively. The model explains 73.1% of behavioural intention to adopt a paid music streaming services and 69% of behavioural intention to recommend its adoption. Hence, the model is able to predict substantive variation of the endogenous variables.

Analysing the path coefficients, it turns out that not all achieved the expected results, as shown in Table 4. Performance expectancy ($\hat{\beta}$ = 0.218, p < 0.05), effort expectancy ($\hat{\beta}$ = 0.073, p < 0.10), hedonic motivation ($\hat{\beta}$ = 0.090, p < 0.10), price value ($\hat{\beta}$ = 0.216, p < 0.05), habit ($\hat{\beta}$ = 0.357, p < 0.05), perceived freemium-premium fit ($\hat{\beta}$ = -0.113, p < 0.05) and attitude towards piracy ($\hat{\beta}$ = 0.109, p < 0.05) were statistically significant in explaining behavioural intention. This model also confirms the hypothesis that behavioural intention ($\hat{\beta}$ = 0.776, p < 0.05) and personalization ($\hat{\beta}$ = 0.112, p < 0.05) have a positive impact in the intention to recommend paid music streaming services to others. Therefore, H1, H2, H5, H6, H7, H8, H10b, H11 and H12 are confirmed by the model. Social influence and facilitating conditions (both UTAUT2 original constructs), as well, involvement and interest and personalization (impact in behavioural intention) were not validated, thus, H3, H4, H9 and H10a are not supported by the model.

The structural model confirms 9 of the 13 hypotheses postulated. H1 to H7 are from the original UTAUT2 theory. This study does not include the effect of age, gender and experience moderators from the UTAUT2 model because it would be an analysis beyond the scope of the main objective of the present research.

Table 4 – Results of the structural model and hypotheses testing.

#	Relationships	Expected sign	Path coeff.	*t*-value	Supported
H1	Performance expectancy → BI	+	0.218	3.965	**Yes***
H2	Effort expectancy → BI	+	0.073	1.896	**Yes****
H3	Social influence → BI	+	-0.014	0.373	No
H4	Facilitating conditions → BI	+	0.016	0.398	No
H5	Hedonic motivation → BI	+	0.090	1.793	**Yes****
H6	Price value → BI	+	0.216	4.537	**Yes***
H7	Habit → BI	+	0.357	7.005	**Yes***
H8	Perceived FP fit → BI	-	-0.113	3.158	**Yes***
H9	Involvement and interest → BI	+	-0.004	0.136	No
H10a	Personalization → BI	+	-0.033	0.874	No
H10b	Personalization → R	+	0.112	3.012	**Yes***
H11	Attitude towards piracy → BI	+	0.109	3.281	**Yes***
H12	Behavioural intention → R	+	0.776	21.923	**Yes***

Note: * $p < 0.05$, ** $p < 0.10$

6. DISCUSSION AND IMPLICATIONS

Since the music industry has gone through changes in all of its areas of operation, streaming has become the most popular way to listen to music. Therefore, in order to help to fill a research gap, the main goal of this study was to shed light on music streaming services adoption process, analysing user's purchase and recommendation intention of a paid version of these services and testing the applicability of the so called UTAUT2 model in this context. Furthermore, additional constructs were identified to possibly improve the model in music streaming services background.

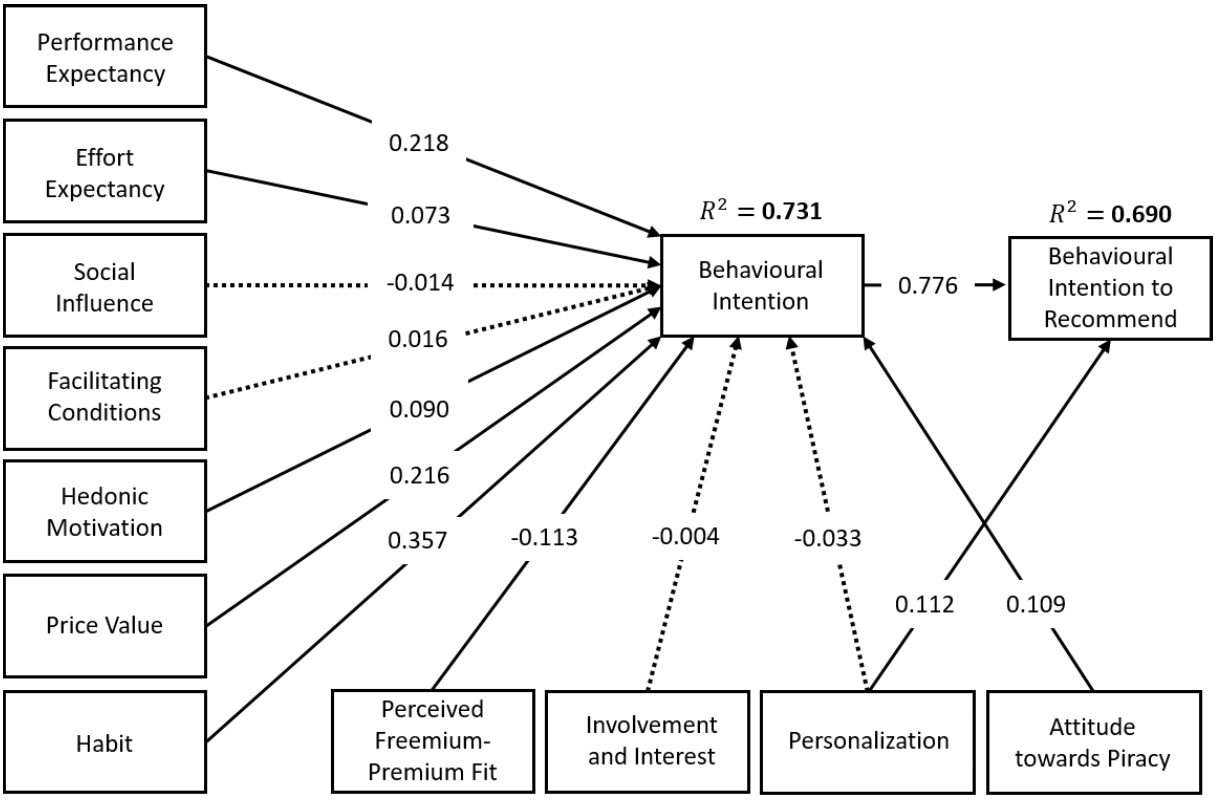

Figure 3 – Structural model results

Note: Paths coefficients that are not statistically significant are in dashed arrows.

Unsurprisingly, the majority of the original constructs of the UTAUT2 model (Venkatesh et al., 2012) showed to be consistent, providing a valuable basis for future research in the music streaming services adoption topic. The results indicate that the variables which explain behavioural intention to buy a premium account are performance expectancy, effort expectancy, hedonic motivation, price value, habit, perceived freemium-premium fit and attitude towards piracy. Behavioural intention to recommend the use of these paid services is confirmed too.

Regarding the endogenous variable behavioural intention, habit, performance expectancy and price value were the most important determinants of intention, being aligned with Venkatesh et al. (2012) findings. However, between them, "habit" revealed to be the strongest determinant ($\hat{\beta}$ = 0.357, $p = 0.000$). Digitalization has deeply revolutionized music consumption by allowing it anytime and everywhere, which was not possible in the past (Cockrill, Sullivan, & Norbury, 2011). Therefore, due to the heavy presence of technology in our lives and prior experiences with it, habit was considered the most important driver for behavioural intention (Hew, Lee, Ooi, & Wei, 2015; Nikou & Bouwman, 2014). In the matter of our study, when a consumer develops a habit of using a music streaming service and for some reason, that service goes from free to paid, we can state that the consumer will be able to pay for it, due to the fact that habit was created (Ye et al., 2004). Hence, it would be important for music streaming services to develop marketing strategies where the desire of using a paid version would be incited to users, in order to create intention and then it would be reflected on effective use.

"Performance expectancy" was accepted as one of the best determinants of behavioural intention ($\hat{\beta}$ = 0.218, $p = 0.000$), corroborating the results of Venkatesh et al. (2012). This means that consumers who perceive benefits from using paid music streaming services, are more likely to use them. Note that the influence of this construct in the behaviour intention is bigger than the effort expectancy, creating the impression that the benefits extracted from the use of these services are more taken into account by consumers than the effort to obtain them. This result contradicts the findings of van der Heijden (2004), where it is affirmed that in hedonic systems (music streaming services can be integrated in this category of systems), the perceived ease of use is understood as a stronger determinant than perceived usefulness. As consumers value efficiency, music streaming providers should focus on designing ways to increase it (Hampton-Sosa, 2017, 2019). It is known that consumer's experience in the IS field is growing and thus, it could be helpful for these services, enhancing their utilitarian character, in order to please more the consumer and to generate differentiation between competitors. In this context, the performance expectancy can be raised through the improvement of tools to look for music, sorting algorithms or by simplifying the share in other platforms (Hampton-Sosa, 2017). The process of discovering new music is indispensable to users (Dias, Gonçalves, & Fonseca, 2017; Hampton-Sosa, 2019; Kjus, 2016), then, the music streaming services should invest in research to discover or improve those kinds of functions. According to Hampton-Sosa (2019), the perceived usefulness of a music streaming service can be interpreted as a decrease in piracy.

Concerning "price value", it was proved that it plays an essential part in the behavioural intention explanation ($\hat{\beta}$ = 0.216, $p = 0.000$). This finding is in line with the previous research performed by Venkatesh et al. (2012), where it was stated that a positive price value means that the advantages of using a technology are perceived to be greater than the monetary cost and therefore, price value impacts positively on intention. That is, if the consumers have a higher perceived value of using a paid music streaming service subscription, it is more probable for them to purchase these services than those who have low perceived value (Wang et al., 2013). Thereby, consumers should feel that a paid subscription adds value compared to the free version (Wang et al., 2005). Weijters & Goedertier (2016) stated that the price impacts consumer's decision on how to access music. According to our results, the price value of a paid music streaming service can be perceived as fair, in consumer's opinion, and not an obstacle for intention to purchase them. In this study, consumers seem to consent that if there is a quality upgrade in the premium version, this version should be fee-based (Ye et al., 2004). Price value has been demonstrated to be a key factor in intention to adopt technology by several studies, thus, researchers and music streaming services should be aware of its utterly importance in the adoption decision field, taking it seriously and carefully as a powerful determinant (Chu & Lu, 2007). According to Chu & Lu (2007), pricing strategies are undoubtedly fundamental for these services, in order to offer realistic prices to consumers. As price value involves a trade-off between perceived sacrifices versus perceived benefits (Li & Cheng, 2014), it is crucial to understand what is taken into account by music streaming services users and from there, identify and segment the costumers, always responding to market changes (Chu & Lu, 2007).

For "perceived freemium-premium fit", its impact was verified in the behavioural intention ($\hat{\beta}$ = -0,113, p = 0.002). Unsurprisingly, the influence of this construct in intention to use a paid music streaming service, is negative. This result is in line with the findings of Wagner et al. (2014), which concluded that the more similar versions are (freemium and premium), the more consumers will create a positive perception about the costless version. In other words, who is more sensitive to restrictions or differences, will be more propene to acquire a paid version of a music streaming service (Wlömert & Papies, 2016). Our result is of absolute importance to the purchase decision due to the fact that it enhances the relevance of the differences between both versions. One way to make the premium features known to users is the offer of a free-trial period (Wagner et al., 2014), where it would be possible to advertise the premium version and create a positive attitude towards it, from the consumer's point of view. According to Wagner et al. 2014, the best approach to increase the conversion of freemium users to premium users is to provide the maximum of premium features. This could become fundamental to raise positive opinions concerning the paid service and thus, to increase the willingness to pay for them. However, this could be a risky strategy, so it is very important to define a limit for the usufruct of all the premium features (Wagner & Hess, 2013). That way, due to the created habit, users will be forced to subscribe to the paid version in order to access all the premium features such as offline access, no advertising and better sound quality (Wagner et al., 2014; Wagner & Hess, 2013). Wagner et al. (2013) suggested that providers should create higher value for paid versions (Wagner, Benlian, & Hess, 2013). Analysing the increasing numbers of Spotify premium users, it seems that its free-trial strategy is working, however, freemium services must still be studied to conclude what strategy is better: to maximize the freemium-premium fit or the offer of a limited free-trial with all premium features.

As for ''personalization'', it is ensured that it impacts significantly the behavioural intention to recommend ($\hat{\beta}$ = 0.112, p = 0.003). This result is in line with the findings of Ball et al. (2006) and Coelho & Henseler (2012), promoting the importance of service personalization in the explanation of the willingness to recommend paid music streaming services. Given this fact, we advise music streaming providers to test personalization programs and if they prove successful, their application in the premium accounts (Ball et al., 2006). It is crucial for marketers to understand what makes users to recommend a service, in order to improve its acceptance (Oliveira et al., 2016).

Regarding "attitude towards piracy", it is shown that this construct plays an important role in explaining behavioural intention ($\hat{\beta}$ = 0.109, p = 0.001), meeting the results of Cesareo & Pastore (2014). The intention to purchase a paid streaming music service is positively influenced by an unfavourable perception of piracy. It seems that a negative impression of music piracy, contributes to the consumer decision of acquiring more ethical means to listen to music. Considering the interview results, it is possible to verify that they are in line with the fact that music streaming can reduce music piracy among young consumers. The more negative a user's attitude is towards music piracy, the more likely they are to pay for a music service. Taking into account the growing numbers of paid music streaming revenues, we can assume that users do not have interest in using illegal ways to access music anymore. However, bearing in mind that both legal and illegal methods to listening to music will continue to coexist (Borja & Dieringer, 2016), it is important to spread education among the youngsters, in order to create awareness about the possible consequences to the music industry and the risks of being punished when using unethical practices (Cesareo & Pastore, 2014). Cesareo & Pastore (2014) recommend that music companies should intensify consumer knowledge by starting marketing campaigns about their legal offers.

Another determinant of behavioural intention is "hedonic motivation" ($\hat{\beta}$ = 0.090, p = 0.073), considering as a significance level, α = 10%. This result is in line with the findings of van der Heijden (2004), Chu & Lu (2007), Venkatesh et al. (2012) and Hampton-Sosa (2017, 2019), evidencing the importance of the role of hedonic benefits in technology acceptance. In this context, some music streaming services features that contribute to their usefulness, can also contribute to the enjoyment of the consumer (Hampton-Sosa, 2019). The offer of tools that can bring joy, as discovery of new music through the recommendation options, the creation of new playlists or reading artist's information, all of it can be fun to the consumer (Hampton-Sosa, 2019). Therefore, listening to music can be enjoyable, so it is considered hedonic consumption (Chu & Lu, 2007). In spite of hedonic motivation importance, in this study, performance expectancy is a stronger determinant of intention, contradicting van der Heijden (2004). However, according to Venkatesh (2012), in a consumer context, both utilitarian and hedonic benefits are significant drivers of technology use. In order to conquer music consumers, music streaming providers should keep in practice some strategies as free-trial programs, to enhance their playfulness to potential subscribers (Chu & Lu, 2007) and emphasizing the existence of pleasurable and emotional features. As an example, Spotify launches at the end of each year the Spotify Wrapped, which consists of a user's summary of their music history, top artists, favourite genres, and total minutes of music - all wrapped in an exciting display (Galant, 2020). This is the fruit of the increase of investments in data-driven innovation to boost users engagement (Ramos & Blind, 2020), deriving into fun ways of using data. With the shareable nature of this campaign, Spotify takes advantage as users organically post their engagement (Galant, 2020).

In line with Venkatesh et al. (2012), "effort expectancy" is statistically relevant in behavioural intention explanation ($\hat{\beta}$ = 0.073, p = 0.058), considering as a significance level, α = 10%. This variable, according to our results, was considered the less important one on impacting intention. Maybe this fact can be justified with the already solid consumer's knowledge in the IT field which leads to less interest in some facilities like tutorials or online support. It is known that for a service to be useful and entertaining, it should also be easy to use (Hampton-Sosa, 2019). Kwong & Park (2008) stated that the easier the service is to use, more confident the consumer will feel about its usage. Therefore, music streaming services should improve their interface in order to create an easier and more intuitive interaction between the user and service. These improvements could pass by better defined music categories that could make the user's discovery of music easier, according to his/her listening history, mood or tastes (Hampton-Sosa, 2019). Another recommendation for music streaming providers to get more user-friendly, could be the facilitation of the payment process, assuring always its security (Oliveira et al., 2016). The importance of effort expectancy was notable too in the interviews, where the participants have referred to the easy access as a perk of music streaming services use.

Although "facilitating conditions" construct was validated in the study of Venkatesh et al. (2012) as a predictor of behavioural intention, the hypothesis corresponding to this variable (H4) has no statistical significance and therefore, has not been confirmed ($\hat{\beta}$ = 0.016, p = 0.691). Facilitating conditions consist of hardware and software availability as well as internet connection, the latter being perceived as a possible limitation (Kwong & Park, 2008). Apparently, if consumers have the required resources to adopt a new technology, they will have the intention to use them (Hew et al., 2015), however, our results suggest that consumers do not consider such aspects when thinking of acquiring a paid streaming music account. Perhaps this could be due to the systematic contact with other technologies, making the experience level very high regarding their use. According to Venkatesh et al. (2003), there are discrepant results relative to this construct and a possible explanation could be that part of the facilitating conditions construct is mistakenly included in the performance expectancy and effort expectancy, resulting in a decrease of importance of it in the prediction of intention.

Another hypothesis that was not accepted by this study is that "social influence" contributes to the behavioural intention ($\hat{\beta}$ = -0.014, p = 0.709), contradicting Venkatesh et al. (2012) and Chen et al. (2018b) findings. The influence of family and friends was not validated in this study and to justify this result, it could be said that this construct seems to be relevant only in the early stages of individual experience (Venkatesh et al., 2003). Our data englobes information from already music streaming users. So, due to the high level of experience in dealing with these services, it is not surprising that the opinion from their peers has not been considered important to the explanation of intention to purchase a paid account. Also, another possible justification could be the hedonic character of these services, revealed in the intrinsic use by each consumer and then, exterior influences are not taken into account by users. However, it is important to keep the positive feedback over time about paid music streaming services in order to attract potential users.

Surprisingly, "involvement and interest" hypothesis was not proved to be relevant in the explanation of behavioural intention ($\hat{\beta}$ = -0.004, p = 0.892), denying Cesareo & Pastore (2014) results. Our questionnaire has revealed strong levels of music interest (mean = 6.10, median = 7), even though we found out that it is not relevant for consumer's intention to pay for a music streaming service. One possible justification could be the fact that people that have a higher involvement with music to derive satisfaction from its consumption, then, this construct could have been confused by hedonic motivation. This result matches the "personalization" outcome, which was not found to be relevant for the explanation of behavioural intention ($\hat{\beta}$ = -0.033, p = 0.382), being in line with Doerr et al. (2010) findings. Both constructs are consistent by not revealing to be important in explaining behavioural intention. One possible interpretation could be the fact that listening to music can be considered a culturally generic activity, not specific enough to these constructs become explanatory variables of the purchase act of a music streaming service (music as a service). Despite this finding, customization topic needs a lot more research on it (Liang et al., 2006) because consumer's interests are in constant change and thus, should be followed for effective personalization to take place (Anand & Mobasher, 2007).

Last but not least, behavioural intention to purchase paid music streaming services positively influences the intention to recommend them ($\hat{\beta}$ = 0.776, p = 0.000). This result is consistent with other studies like Miltgen et al. (2013) and Oliveira et al. (2016). Recommendation power is hardly ever considered in technology acceptance, despite its relevance (Miltgen et al., 2013). In the music streaming services field, the potential of recommendation has been ignored over time. Therefore, this study indicates the importance of this issue in future research. Our results prove that the intention to use paid music streaming services activates the intention to recommend their use, by word-of-mouth, social networks or other convenient ways of communication. This could suggest that consumers who have the intention to purchase a paid music streaming account, will be more prone to recommend them to their peers and therefore, successfully start a snowball effect.

7. LIMITATIONS AND FURTHER RESEARCH

Like other empirical studies, there are some limitations in our research which need to be considered. Firstly, a convenience sampling method was used. Therefore, we recommend caution in analysing the findings. Secondly, our research is centred on practical factors and thus, the moderators of the UTAUT2 model (age, gender and experience) did not constitute the target of this analysis, and consequently were not taken into account. This could be assumed as a limitation of our proposed extended model, according to the theory. Even though, we believe that it does not implicate the legitimacy of the obtained results but it would be interesting to compare our findings with the moderator's effect in a next investigation.

Future research may consist in the adaptation of this study to other locations and submit it to a larger number of participants, in order to assure generalization of results. This study could be used as a basis for upcoming analysis by improving the model and testing it in some specific countries and age groups (Naranjo-Zolotov et al., 2019). It would be interesting to analyse the differences between actual users of paid music streaming services and the freemium users, in order to understand which factors weigh more for each one and make possible the implementation of different marketing strategies. The addition of new constructs to the present model would be helpful to try to increase the predictive power of our framework. In a while, it might be interesting to go deep about the effect of the paid music streaming services in the abolition of music piracy, in order to verify, namely, if this tendency of decrease remains. Intention to recommend should be better explored in this context as its effect is not well known in the field of technology acceptance yet.

8. CONCLUSIONS

This study sought to analyse which factors influence the intention to purchase of a music streaming service and, consequently, its recommendation. To this end, several hypotheses were tested, using a research model based on UTAUT2. Through the analysis of our results, it is possible to retain some important insights which could be pertinent for music streaming services providers to perceive the adoption process behaviour of users. The contribution of this research may be useful to the scientific community and technology developers, bringing valuable knowledge to the design of music streaming services regarding user's expectations and preferences (Nikou & Bouwman, 2014).

Furthermore, our findings suggest that the original constructs of the UTAUT2 model are important determinants of music consumption behaviour, except facilitating conditions and social influence, for the reasons previously mentioned. This means that it is verified the applicability of this model in the music streaming services context. The main finding of this study is that habit plays the most important role in influencing the intention to use a paid music streaming service. Other relevant determinants of behaviour intention are performance expectancy, price value, attitude towards piracy, hedonic motivation and effort expectancy, in order of significance. Involvement and interest and personalization have not revealed to be important in users' decision to acquire a paid account of a music streaming service, however, personalization contributes to the willingness to recommend these services.

To conclude, we can state that this subject is complex and a lot of variables are involved in the consumer's intention to purchase a music streaming service nowadays. However, the music streaming services providers should continue bonding with users and potential users, focusing on their needs and creating satisfaction and trust concerning the paid versions. It is fundamental to fortify habit, making it repetitive and to invest in research about the relevant constructs. In this way, it will be possible to increase the number of recommendations in social networks or by word-of-mouth, helping the acceptance and recognition of these paid services.

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10. APPENDIX

APPENDIX A. CONSTRUCTS, ITEMS AND REFERENCES EMPLOYED

Constructs	Code	Items	References
Performance Expectancy (PE)	PE1	I find paid music streaming services useful in my daily life.	(Venkatesh et al., 2012)
	PE2	Using paid music streaming services help me accomplish things more quickly.	
	PE3	Using paid music streaming services increase my productivity /performance.	
	PE4	A paid music streaming service allows me to listen to music with good sound quality.	(Widodo, Setiadjie, & Sary, 2017)
	PE5	Overall, a paid music streaming service is advantageous.	(Leong, Hew, Tan, & Ooi, 2013)
Effort Expectancy (EE)	EE1	Learning how to use paid music streaming services is easy for me.	(Venkatesh et al., 2012)
	EE2	My interaction with paid music streaming services is clear and understandable.	
	EE3	I find paid music streaming services easy to use.	
	EE4	It is easy for me to become skilful at using paid music streaming services.	
Social Influence (SI)	SI1	People who are important to me think that I should use paid music streaming services.	(Venkatesh et al., 2012)
	SI2	People who influence my behaviour think that I should use paid music streaming services.	
	SI3	People whose opinions that I value prefer that I use paid music streaming services.	
	SI4	Subscribing a paid music streaming service would make a good impression on other people.	(Lin & Huang, 2011)
Facilitating Conditions (FC)	FC1	I have the resources necessary to use paid music streaming services.	(Venkatesh et al., 2012)
	FC2	I have the knowledge necessary to use paid music streaming services.	
	FC3	A paid music streaming service is compatible with other technologies I use.	
	FC4*	I can get help from others when I have difficulties using paid music streaming services.	
Hedonic Motivation (HM)	HM1	Using paid music streaming services is enjoyable.	(Venkatesh et al., 2012)
	HM2	Using paid music streaming services is exciting.	
	HM3	Using paid music streaming services is pleasant.	(van der Heijden, 2004)
	HM4	Using paid music streaming services is interesting.	
Price Value (PV)	PV1	A paid music streaming service is reasonably priced.	(Venkatesh et al., 2012)
	PV2	A paid music streaming service is a good value for the money.	
	PV3	At the current price, a paid music streaming service provides a good value.	
Habit (HT)	HT1	The use of paid music streaming services has become a habit for me.	(Venkatesh et al., 2012)
	HT2	I am addicted to using paid music streaming services.	
	HT3	I must use paid music streaming services.	
	HT4	Using paid music streaming services is something I do without thinking.	(Verplanken & Orbell, 2003)
Perceived freemium-premium fit (PF)	PF1	There is a big similarity between the functionalities of the free version and those of the premium version of a music streaming service.	(d'Astous & Landreville, 2003; Wagner et al., 2014)
	PF2	There is a good association between the free version of a music streaming service and the premium version.	
	PF3	The free version of a music streaming service differentiates strongly from the premium version.	
	PF4*	I prefer to deal with ads and other restrictions than paying for a music streaming service.	Adapted from the interviews
Involvement and Interest (II)	II1	I have a strong interest in music.	(Styvén, 2010)
	II2	I value music as an important part of my lifestyle.	
	II3	The music I hear says a lot about me.	

Personalization (P)	P1	It is important for me to be able to customize my account on a music streaming service.	Adapted from the interviews
	P2	It is important for me the suggestion of songs, artists or podcasts by the music streaming service.	
	P3	It is important for me to be able to create customized playlists.	
	P4	It is important for me to get information about the bands/musicians I follow.	
	P5*	It is important for me to be able to access the activity of people I follow.	
	P6*	It is important for me to be able to share music, playlists or podcasts on social networks.	
Attitude towards piracy (AP)	AP1	I make a special effort to financially support the artists.	(Lin & Huang, 2011)
	AP2	I have avoided the practice of illegal downloads because it has potentially harmful effects for artists.	
	AP3	The risk associated to music piracy affects the likelihood of my involvement in it.	(Borja et al., 2015)
	AP4*	I do not believe that there is a high risk of getting caught in the practice of piracy.	(Borja & Dieringer, 2016; Borja et al., 2015)
	AP5*	I do not believe that the consequences will be very severe if I do get caught.	
	AP6*	Downloads do not harm artists because they are already too successful.	
	AP7*	I have a positive perception towards illegal downloads.	(Liao & Hsieh, 2013)
Behavioral intention (BI)	BI1	I intend to continue using paid music streaming services in the future.	(Venkatesh et al., 2012)
	BI2	I will always try to use paid music streaming services in my daily life.	
	BI3	I plan to use paid music streaming services in the near future.	
Behavioral intention to recommend (R)	R1	Usually I recommend using paid music streaming services.	(Johnson, Herrmann, & Huber, 2006)
	R2	I would recommend paid streaming music services to someone who seeks my advice	(Hoehle & Venkatesh, 2015; Johnson et al., 2006)

*: Removed items

APPENDIX B. CROSS-LOADINGS

Items	PE	EE	SI	FC	HM	PV	HT	PF	II	P	AP	BI	R
PE1	**0.869**	0.418	0.426	0.433	0.572	0.627	0.656	-0.344	0.210	0.394	0.259	0.720	0.687
PE2	**0.743**	0.295	0.368	0.282	0.457	0.429	0.397	-0.363	0.102	0.310	0.254	0.480	0.478
PE3	**0.835**	0.295	0.394	0.295	0.462	0.475	0.553	-0.332	0.225	0.397	0.224	0.553	0.510
PE4	**0.815**	0.363	0.340	0.339	0.469	0.403	0.426	-0.279	0.082	0.288	0.147	0.541	0.496
PE5	**0.902**	0.376	0.421	0.437	0.598	0.595	0.589	-0.390	0.125	0.374	0.196	0.688	0.651
EE1	0.338	**0.868**	0.208	0.540	0.401	0.290	0.250	-0.111	0.127	0.330	0.135	0.347	0.299
EE2	0.437	**0.909**	0.263	0.571	0.495	0.369	0.389	-0.187	0.181	0.368	0.149	0.461	0.406
EE3	0.377	**0.925**	0.187	0.555	0.453	0.285	0.278	-0.176	0.154	0.339	0.119	0.384	0.340
EE4	0.324	**0.823**	0.157	0.486	0.363	0.224	0.288	-0.168	0.122	0.335	0.070	0.320	0.299
SI1	0.463	0.237	**0.897**	0.242	0.393	0.406	0.428	-0.220	0.114	0.288	0.304	0.437	0.479
SI2	0.421	0.181	**0.916**	0.263	0.382	0.408	0.393	-0.176	0.041	0.283	0.233	0.395	0.459
SI3	0.427	0.254	**0.941**	0.269	0.400	0.393	0.422	-0.233	0.095	0.273	0.216	0.431	0.478
SI4	0.300	0.124	**0.722**	0.169	0.317	0.251	0.300	-0.168	0.087	0.257	0.102	0.245	0.308
FC1	0.387	0.375	0.231	**0.845**	0.329	0.506	0.404	-0.207	0.097	0.335	0.237	0.472	0.437
FC2	0.312	0.621	0.188	**0.827**	0.384	0.295	0.278	-0.117	0.119	0.296	0.130	0.313	0.300
FC3	0.389	0.603	0.268	**0.847**	0.394	0.338	0.324	-0.101	0.169	0.302	0.156	0.366	0.412
HM1	0.588	0.548	0.351	0.497	**0.868**	0.506	0.441	-0.255	0.073	0.323	0.177	0.581	0.529
HM2	0.459	0.286	0.392	0.234	**0.819**	0.390	0.384	-0.267	0.148	0.294	0.235	0.439	0.428
HM3	0.547	0.467	0.362	0.401	**0.897**	0.458	0.408	-0.264	0.078	0.297	0.125	0.512	0.476
HM4	0.553	0.383	0.398	0.351	**0.905**	0.505	0.489	-0.314	0.136	0.357	0.189	0.547	0.530
PV1	0.568	0.312	0.381	0.434	0.493	**0.961**	0.495	-0.301	0.110	0.356	0.303	0.630	0.614
PV2	0.596	0.343	0.396	0.460	0.509	**0.967**	0.536	-0.380	0.147	0.396	0.334	0.666	0.654
PV3	0.620	0.321	0.453	0.463	0.547	**0.964**	0.597	-0.346	0.152	0.391	0.357	0.699	0.663
HT1	0.667	0.390	0.395	0.472	0.511	0.618	**0.889**	-0.284	0.226	0.403	0.219	0.774	0.687
HT2	0.531	0.259	0.390	0.297	0.434	0.419	**0.883**	-0.259	0.247	0.384	0.245	0.588	0.529
HT3	0.503	0.233	0.413	0.256	0.382	0.419	**0.867**	-0.249	0.220	0.362	0.237	0.562	0.498
HT4	0.510	0.304	0.372	0.371	0.386	0.481	**0.862**	-0.278	0.182	0.323	0.161	0.611	0.560
PF1	-0.210	-0.035	-0.103	-0.027	-0.180	-0.192	-0.108	**0.694**	-0.013	-0.097	-0.018	-0.236	-0.196
PF2	-0.138	-0.017	-0.044	0.015	-0.104	-0.151	-0.075	**0.695**	-0.005	-0.034	0.036	-0.169	-0.163
PF3	-0.440	-0.246	-0.267	-0.252	-0.330	-0.366	-0.367	**0.846**	-0.192	-0.375	-0.182	-0.450	-0.427
II1	0.185	0.175	0.089	0.173	0.129	0.140	0.241	-0.130	**0.968**	0.290	0.219	0.218	0.246
II2	0.173	0.154	0.092	0.134	0.113	0.149	0.261	-0.151	**0.968**	0.292	0.227	0.209	0.253
II3	0.093	0.097	0.074	0.038	0.055	0.045	0.099	-0.035	**0.628**	0.288	0.149	0.067	0.082
P1	0.310	0.299	0.257	0.258	0.274	0.252	0.343	-0.235	0.287	**0.784**	0.214	0.290	0.309
P2	0.353	0.329	0.265	0.345	0.293	0.392	0.330	-0.233	0.199	**0.821**	0.270	0.367	0.349
P3	0.383	0.371	0.241	0.346	0.351	0.326	0.392	-0.257	0.259	**0.846**	0.243	0.391	0.421
P4	0.326	0.252	0.258	0.251	0.256	0.304	0.300	-0.240	0.287	**0.790**	0.309	0.322	0.345
AP1	0.266	0.168	0.230	0.256	0.177	0.333	0.270	-0.106	0.238	0.328	**0.881**	0.363	0.347
AP2	0.205	0.095	0.206	0.162	0.194	0.283	0.181	-0.090	0.179	0.221	**0.886**	0.296	0.265
AP3	0.106	0.019	0.194	0.023	0.110	0.180	0.087	-0.112	0.107	0.204	**0.611**	0.138	0.138
BI1	0.695	0.394	0.422	0.442	0.582	0.662	0.725	-0.402	0.191	0.392	0.297	**0.965**	0.795
BI2	0.696	0.399	0.415	0.419	0.569	0.634	0.687	-0.434	0.211	0.404	0.379	**0.957**	0.788
BI3	0.703	0.460	0.441	0.491	0.578	0.695	0.706	-0.412	0.202	0.432	0.354	**0.958**	0.791
R1	0.673	0.368	0.485	0.448	0.565	0.651	0.654	-0.382	0.246	0.432	0.311	0.810	**0.976**
R2	0.669	0.386	0.496	0.461	0.539	0.653	0.633	-0.401	0.233	0.433	0.342	0.798	**0.975**