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Research article

Music streaming services: understanding the drivers of customer purchase and intention to recommend

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ABSTRACT

The music industry has undergone tremendous 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 of 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 its business development. This study aims to understand the factors that influence music consumption through streaming platforms, particularly studying the intention to adopt premium (paid) versions of a music streaming service and recommend them. An extension of the UTAUT2 model (version of the Unified Theory of Acceptance and Use of Technology, applied to the consumer side) was created. Based on data collected from 324 music streaming services users, the framework of this study was tested using structural equation modelling (SEM). Research also included in-depth semi-structured interviews in order to generate a more profound knowledge about the profile, behaviours and motivations of the new music consumer. Our findings confirm that habit, performance expectancy and price value play the most important role in influencing the intention to use a paid music streaming service. Simultaneously, new dimensions such as personalisation, attitude towards piracy and perceived freemium-premium fit arise as having an additional relevant role in adopting this type of service. The research contributes insights into music streaming services consumer behaviour, providing several theoretical and practical implications to music streaming services providers.

1. Introduction

Since the beginning of the oldest societies, music has played a fundamental role in the life of human beings, being undeniably a form of universal expression that unites old and future generations culturally and emotionally (Larsen et al., 2009, 2010; Naveed et al., 2017). The importance of music in our society has led to creating an industry that includes all the concepts inherent to this thematic, such as its organisation, distribution, and profitability. This industry, made up mostly of countless record labels, has experienced golden times through sales of physical copies, thus monopolising 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 for this industry as we knew it has become limited, and a reinvention of it was mandatory (Warr and Goode, 2011). The decrease in the volume of revenues, mainly due to the lower number of sales of physical copies (Sinclair and Tinson, 2017), led the main record labels to modernise. In particular, the growth of streaming services has revolutionised consuming music, as the number of users of these services keeps increasing (IFPI, 2021). It is known that since 2010, the number of users of the Spotify streaming platform has increased from 15 to 100 million worldwide (Aguiar and Waldfogel, 2018).

These platforms are based on a relatively recent business model (Sinclair and Tinson, 2017) that basically consists of the service proposal according to two modalities: adoption of an account exempt from monthly costs, but in return, users are exposed to advertising and other types 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 et al., 2010; Hamari et al., 2017; Sinclair and Tinson, 2017; Wagner et al., 2014), with this modality contributing to a substantial increase in the profits of this industry (Arditi, 2018; Wlömert and Papies, 2016).

The aim of freemium is to attract the largest possible number of users (Chen et al., 2018a, 2018b; Kumar, 2014), increasing the probability of many upgrading to a premium account (Anderson, 2009; Dinsmore et al., 2017; Wagner and Hess, 2013), where there are several advantages like no advertising, better sound quality and the possibility of offline access

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(Dörr et al., 2013; Wagner et al., 2014). However, it is still unclear how choosing between accounts is done; thus, it is crucial for music streaming companies to understand consumers' motivations in order to convert free users into paid subscribers (Chen et al., 2018b).

By analysing music streaming services revenue data, it becomes impossible to ignore its current value. According to statistics obtained from the International Federation of the Phonographic Industry (IFPI) official website, it is observed that in 2020, 62.1% of the profits of this industry were garnered through streaming services (IFPI, 2021). It is visible that this new method of listening to music has radically changed the paradigm of this industry (Tschmuck, 2012; Wlömert and Papies, 2016).

In 2020, using these services through a paid subscription had consistently increased, around 18.5%, compared to 2019, with the tendency for this value to continue to rise (IFPI, 2021). By analysing data from the same source, it is known that revenue from the sale of physical copies decreased by 4.7%, with digital music downloads following the same downward trend: around minus 15.7%, in the year 2020, throughout the world (IFPI, 2021). In 2020, revenues from streaming for this industry grew by 19.9% due to an 18.5% increase in premium streaming accounts (IFPI, 2021). 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 et al., 2017) and by not needing to own the music file (Dörr et al., 2013).

One issue about music digitalisation is that it has given rise to a high wave of file piracy, with the authors being the most prominent 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 invest in this type of research in order to understand the streaming relation towards music piracy better (Borja et al., 2015; Sinclair and Green, 2016). It is said that the use of legal platforms for these services may appeal to an end to music piracy (Wlömert and 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 and Ordanini, 2003; Wang et al., 2013b). These new consumer practices are recent, implying that the level of information surrounding this topic is not yet sufficiently abundant and systematic (Sinclair and Green, 2016). There is little research on the willingness to pay for services when a free version is available (Chen et al., 2018a, 2018b; Dörr et al., 2013), as well as the new freemium model (Doerr et al., 2010; Oestreicher-singer & Zalmanson, 2013; Wagner et al., 2014). In fact, despite previous attempts to better understand the use of streaming music services, there is a distinct gap of knowledge about what the effective drivers of adoption and recommendation of paid streaming music services are, and to which extent “acceptance of use” models may be applied in this context or not. 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 undergone, this study aims to shed light on 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 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 et al., 2013; Wang et al., 2005; Wang et al., 2013). Based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), a new extended model is conceptualised and tested, using data collected from 324 music streaming services users. The contribution of this study is, therefore, two-fold. Firstly, we investigate the determinants of paid music streaming services adoption using an innovative model that may be seen as an extension of the UTAUT2 framework, including new drivers that may increase the significance and predictability of results. Secondly, we have included a component of intention to recommend as a second dependent variable, filling an additional gap of great interest for business strategies. In fact, recommending a technology to others is a behaviour that has been significantly neglected by researchers (Luo et al., 2016), and to the best of our knowledge, it is the first time that this post-adoption behaviour has been studied in the context of music streaming.

The remainder of this paper is structured as follows. First, we provide the conceptual background through a deeper analysis of music streaming services and technology adoption models. 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 considerably in the last few years. New concepts of digital music distribution have been established recently, 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 full-time access instead of physical property ownership (Sinclair and Tinson, 2017). From the physical format to the digital era, the increase and ease of access to the internet were fundamental for all these changes to be possible, namely the appearance of legal streaming platforms (Hamari et al., 2016; Sinclair and Tinson, 2017). One factor contributing to this phenomenon of information and content expansion (in this specific case, musical) is the constant use of technology through smartphones (Johansson et al., 2019).

A music streaming service offers several functions to its users, the main focus being the supply of extensive libraries of songs and albums through an internet connection (Zimmer, 2018). Nowadays, these services are the fastest growing music option (Cesareo and Pastore, 2014). There are two types of streaming services users: those who subscribe to an account exempt from usufruct fees and financed by advertising and those who sign up for 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 kinds 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 its free version (Ye et al., 2004). Currently, the most popular music streaming service globally 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, 35% European, 26% North American, 22% Latin American and 17% 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% (this fell short of 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 the previous 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 et al., 2016). Thus, there is nothing more important for this industry, such as analysing and interpreting consumer behaviour to understand the role of music streaming services in the face of illegal music downloads (Sinclair and 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 digitalisation process that the music industry has experienced, the need to understand the process of adopting online music streaming services better, 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 adopting technology were applied. The basic concept of technology adoption can be described as the combination of individual reactions, intentions to use and actual use (Venkatesh et al., 2003).

One of the most fundamental adoption theories is the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975), being used as a basis for many other adoption theories about consumer behaviour. Cesareo and 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.

The Theory of Planned Behaviour (TPB) (Ajzen, 1991) is an extension of the previous TRA and has been applied in several studies within the music streaming services adoption context (Cronan and Al-Rafee, 2008; Dörr et al., 2013; Kwong and Park, 2008; Lin et al., 2013; Peace et al., 2003; Plowman and Goode, 2009; Wagner and Hess, 2013; Yoon, 2011). Also, the Technology Acceptance Model (TAM) (Davis, 1989) is one of the most important models in the context of technology adoption and use (Cheong and Park, 2005), based on TRA. Some derivations of this model, like TAM2, have also been proposed (Venkatesh and Bala, 2008; Wang, 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) and SCT (Social Cognitive Theory). Consisting of four constructs: performance expectancy, effort expectancy, social influence and facilitating conditions, UTAUT obtained satisfactory results (Venkatesh et al., 2003; Venkatesh et al., 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.

After UTAUT's release, the model was tested in different contexts and in 2012, it was extended to the consumer context, developing 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 primarily due to its ability to adapt to various technologies and its orientation to the consumer's perspective. Venkatesh et al. (2012) claimed that for future research, in order to amplify the theory development (UTAUT2), it could be tested in different countries, in groups of different ages and with different technologies. Therefore, this study aims to apply UTAUT2 to the music streaming services panorama and identify relevant factors that can be useful in the applicability of UTAUT2 in that context (see Figure 1).

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 recommend it. Those variables were found in the literature review and the previously conducted semi-structured interviews. The conceptual model is shown in Figure 2.

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

3.1. UTAUT2 variables

3.1.1. Performance expectancy

Performance expectancy is defined as the degree to which using technology will benefit consumers in performing certain activities (Venkatesh et al., 2012). According to Chu and Lu (2007), perceived usefulness (a 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 and Lu, 2007). Although online music services aim to deliver an entertaining experience, they also provide functional benefits to people (Chu and Lu, 2007). Hampton-Sosa (2019) asserted that perceived usefulness and perceived enjoyment lead to purchasing a music streaming service (Hampton-Sosa, 2019). Some attributes from the utilitarian character of the music streaming services are tools to find music, organise 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 and Oliveira, 2015; Luo et al., 2010). Hence, we formulate the following hypothesis:

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

3.1.2. Effort expectancy

Effort expectancy is described as the degree of ease associated with consumers' use of technology (Venkatesh et al., 2012). According to Kwong and 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 and Park, 2008). The same authors stated that access to online music should be effortless and that service quality creates a belief in the users that the service is easier to use (Kwong and Park, 2008). Davis (1989) claimed that if an IS is deemed 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 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).

3.1.3. 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 a certain behaviour or not (Ajzen, 1991; Fishbein and Ajzen, 1975). Several studies in the entertainment

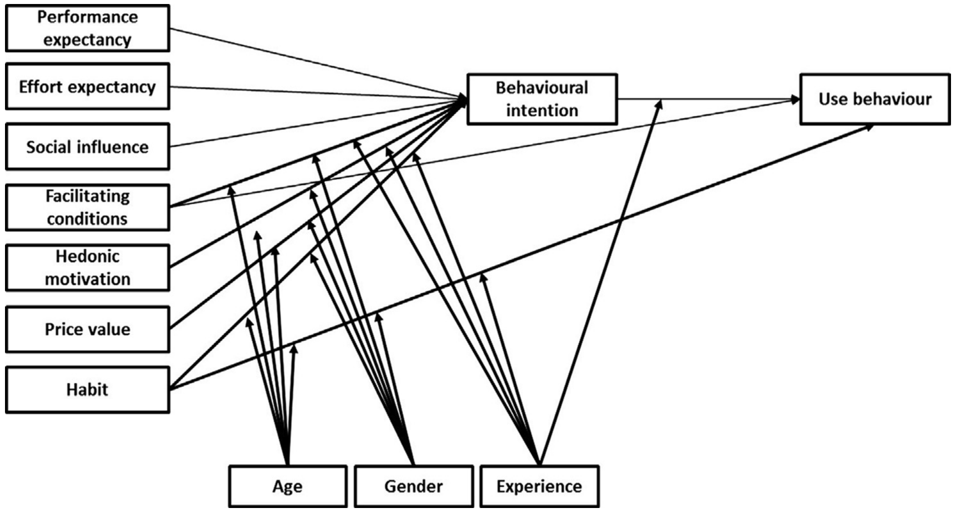

Figure 1. UTAUT2 model.

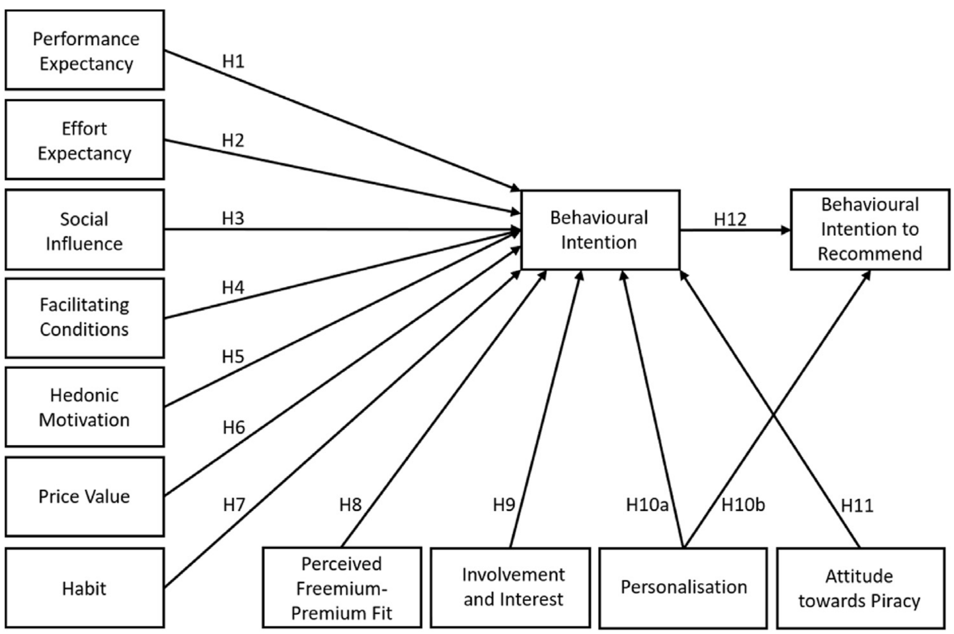

Figure 2. Research model.

field proved its relevance (Chen et al., 2018b; Dörr et al., 2013; Kwong and Park, 2008; Molteni and Ordanini, 2003; Yang, 2013). Therefore, we hypothesise:

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

3.1.4. 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 designed to remove barriers to use (Venkatesh et al., 2003). A consumer with 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 and Park, 2008). Therefore, we hypothesise:

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

3.1.5. Hedonic motivation

Hedonic Motivation is defined as the fun or pleasure derived from using a technology (Venkatesh et al., 2012). In this context, it is the degree to which a user expects enjoyment from listening to streamed music (Chen et al., 2018b). Music streaming services can be considered a 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 conceptualised as perceived enjoyment (van der Heijden, 2004; Venkatesh et al., 2012) and is often considered a reliable predictor of technology adoption (Chen et al., 2018b; van der Heijden, 2004). It has been considered one of the most important determinants of acceptance and use (Brown and 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 hypothesise:

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

3.1.6. 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 et al., 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 et al., 2003; Chiang and Assane, 2009; Doerr et al., 2010; Dörr et al., 2013; Papies et al., 2011; Sinha and Mandel, 2008; Wagner and Hess, 2013; Weijters and 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, it makes sense that price value also determines users' intention to purchase the premium version. The price value is favourable when the benefits of using technology are perceived to be greater than the monetary cost (Venkatesh et al., 2012). Therefore, we hypothesise:

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

3.1.7. 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 and Malhotra, 2005), impacting behavioural intention (Venkatesh, 2000). Habit's influence as a predictor of intention has been analysed in several studies (Kim et al., 2005; Kim and Malhotra, 2005; Limayem et al., 2007; Limayem and 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 hypothesise:

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

3.2. Extensions

The following new constructs have been considered as possible extensions to the basic UTAUT2 framework. By introducing new dimensions from previous theoretical and empirical research, we aim to increase significance and predictability of results in the context of music streaming services purchase and recommendation.

3.2.1. 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 free and paid version features, 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 limiting 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 freemium-premium fit is high, the user will adopt the free version and, thus, will create a positive behaviour towards the same (Hamari et al., 2020; Wagner et al., 2014). Consumers take this measure into account when purchasing a service with a free version available (d'Astous and 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 and Tang, 2010; Wagner et al., 2014; Wang et al., 2013a). According to Wlömert and Papies (2016), greater sensitivity to restrictions means a greater propensity to subscribe to a premium account (Wlömert and Papies, 2016). In the previously carried out in-depth semi-structured interviews, 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 and 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 et al., 2013). Therefore, we hypothesise:

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

3.2.2. 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 evaluate its advantages and/or disadvantages (Bian and Moutinho, 2009; Cesareo and Pastore, 2014). Styvén (2010) states that an individual involved in the music subject will be more likely to acquire technologies in relation to it in all formats (Styvén, 2010). Aguiar and Martens (2016) also suggest that consumers with a greater interest in music assimilate streaming as a means to acquire digital music (Aguiar and Martens, 2016). In a study carried out by Cesareo and 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 and Pastore, 2014). The results were favourable, and thus, we hypothesise:

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

3.2.3. Personalisation

Personalisation 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 and Marshall, 2006). It is a marketing strategy where consumer information is used to create appropriate solutions (Peppers and Rogers, 1997; Vesanen, 2007). Personalisation needs to be adapted to the dynamic user interests (Anand and Mobasher, 2007). The possibility of personalisation has a substantial impact on music streaming services users (Lee and Waterman, 2012), with the creation of automatic playlists based on recommendation algorithms being important for them (Prey, 2018). Some customisable features could only be 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 personalisation on behavioural intention to recommend a service has also been argued. It is known that the effect of service personalisation on loyalty exists (Ball et al., 2006; Coelho and 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 personalisation 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 personalisation is useful to consumer satisfaction (Anand and Mobasher, 2007; Liang et al., 2006), therefore, to obtain more insights about the use of these services, we propose the following hypotheses:

H10a. Personalisation (P) is positively related to behavioural intention (BI).

H10b. Personalisation (P) is positively related to behavioural intention to recommend (R).

3.2.4. Attitude towards piracy

Attitude toward a behaviour is construed 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 and 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 a low cost, if not free of charge (Aguiar and Waldfogel, 2018). The music industry sees this impact with optimism (Sinclair and Green, 2016). However, Borja & Dieringer (2016) stated that, possibly, these two ways of acquiring music, viz. piracy or streaming, will keep coexisting (Borja and Dieringer, 2016). According to Weijters et al. (2014), consumers tend to prefer ethical and legal options, if possible (Weijters et al., 2014). The attitude of individuals towards digital piracy was found to be influenced by perceived benefits, perceived risk, and habit (Yoon, 2011). Cesareo and Pastore (2014) declared that a positive attitude towards piracy negatively influences the intention to subscribe to a paid music streaming service (Cesareo and Pastore, 2014), the most important variables to explain attitude towards piracy being mainly of an economic nature (Sinha and Mandel, 2008; Weijters et al., 2014). Borja and Dieringer (2015) concluded that college students commonly think of piracy as an attitude that does not harm artists. However, the same authors maintained that most consumers are aware that there is a risk (Borja et al., 2015). Aguiar and Martens (2016) found evidence of a positive relationship between music streaming platforms and purchases of licensed music. Peace et al. (2003) proved that punishment severity and punishment certainty directly affect the individual's attitude toward software piracy. Therefore, after this review on existing research, we hypothesise:

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

3.2.5. Behavioural intention to recommend

Recommendation is recognised as a key post-adoption behaviour (Luo et al., 2016). Previous research assumed that consumers with a higher intention to adopt new technology are more likely to become adopters of the technology (Kuo and Yen, 2009; Miltgen et al., 2013; Oliveira et al., 2016) and then, to recommend it to others (Miltgen et al., 2013; Oliveira et al., 2016). It is paramount to underline that social media has completely changed how society communicates and exposes its ideas or businesses (Olanrewaju et al., 2018; Zheng et al., 2015). A positive recommendation or feedback from a friend seems to influence music purchase decisions (Dewan and Ramaprasad, 2014). It is known that the recommendation effect is under research (Luo et al., 2016), mainly due to the focus on the user behaviour construct (Naranjo-Zolotov et al., 2019). Therefore, we hypothesise:

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 of a combination of qualitative and quantitative research designs. The study was approved by Nova Information Management School Ethical Committee.

4.1. Qualitative research

Qualitative analysis was based on a literature review and semi-structured in-depth interviews about music streaming services, music piracy and social media. These were of utmost importance to understand the opinion and perspective of the participants, making it possible to retain information about how 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 aged between 18-24 years (thirteen participants), 25–34 (five participants), 35–44 (one participant) and >50 (one participant) were interviewed. The sample was gender-balanced. All members hold Portuguese nationality and live in Lisbon. The interview guide was divided in three sections. The first part referred to the participants' social media engagement and their music consumption habits. Then, respondents were asked about their opinions concerning music streaming services. Finally, participants were invited to talk about how they perceive illegal downloads. Each interview took twenty minutes, on average.

The semi-structured interview guide comprised only open-ended questions, and its design took into account former research findings in the academic literature and published practitioner reports (InSites Consulting, 2012; Socialbakers, 2015). A purposeful sampling process was applied, seeking to select the most productive sample for answering the questions (Clark, 2003). The interviewing process stopped when the data achieved saturation, i.e., when no new information emerged (Clark, 2003; Krueger and Krueger, 2002). Although saturation was obtained with fewer than 20 interviews, the researchers decided to ensure a minimum of 20 interviews.

4.2. Quantitative research

A questionnaire was distributed to a sample of members of the target population. The questionnaire was designed around the proposed conceptual model. The indicators for each construct were adapted from literature (Table 1), with 53 indicators distributed in a total of 13 constructs. Items concerning performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, habit and behavioural intention were partially adapted from Venkatesh et al. (2012). Several complementary items from additional sources were included for some of these constructs. Performance expectancy also benefitted from the investigations of Widodo et al. (2017) and Leong et al. (2013), social influence from Lin and Huang (2011), hedonic motivation from van der Heijden (2004) and habit from Verplanken and Orbell (2003). Items for perceived freemium-premium fit were adapted from d'Astous and Landreville (2003), Wagner et al. (2014) and partially self-developed from the qualitative research. Items for involvement and interest resulted from Styvén (2010), attitude towards piracy items were based on Lin and Huang (2011), Borja et al. (2015), Borja and Dieringer (2016) and Liao and Hsieh (2013), and behavioural intention to recommend has items adapted from Johnson et al. (2006), Hoehle and Venkatesh (2015) and Johnson et al. (2006). Finally, personalisation was represented by self-developed items built over the qualitative research.

The scale chosen to measure responses was the 7-Point Likert type scale: strongly disagree to strongly agree. The questionnaire was drafted in English and reviewed for content validity by language experts from a university. Because the questionnaire was administered in Portugal, the English version of the instrument was translated into Portuguese by a professional translator. The questionnaire was then reverse translated into English to confirm translation equivalence. The questionnaire was pilot tested with a sample of 20 subjects to optimise the instrument. Results confirm that the scales were reliable and valid. The questionnaire was launched online on social networks and also sent by email to university students. Thus, the sampling process used in this study was non-probabilistic (Iacobucci and Churchill, 2018). The survey was active for one month (August 21 to September 21, 2020) on the Qualtrics platform. Demographic and social questions were included in order to be more sensitive about sample characteristics and envision some possible research hypotheses in the future. By not defining age limits, it was possible to acquire a greater variety of responses.

Table 1. Constructs, items and references used.

Constructs	Code	Items	References
Performance Expectancy (PE)	PE1	I find paid music streaming services useful in my daily life.	(Venkatesh et al., 2012) (Widodo et al., 2017) (Leong et al., 2013)
	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.	
	PE5	Overall, a paid music streaming service is advantageous.	
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) (Lin and Huang, 2011)
	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.	
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) (van der Heijden, 2004)
	HM2	Using paid music streaming services is exciting.	
	HM3	Using paid music streaming services is pleasant.	
	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 good value for money.	
	PV3	At the current price, a paid music streaming service provides good value.	
Habit (HT)	HT1	The use of paid music streaming services has become a habit for me.	(Venkatesh et al., 2012) (Verplanken and Orbell, 2003)
	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.	
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 and Landreville, 2003; Wagner et al., 2014) Adapted from the interviews
	PF2	There is a good association between the free version of a music streaming service and the premium version.	

(*continued on next page*)

Table 1 (*continued*)

Constructs	Code	Items	References
	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.	
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 listen to says a lot about me.	
Personalisation (P)	P1	It is important for me to be able to customise my account on a music streaming service.	Adapted from the interviews
	P2	The suggestion of songs, artists or podcasts by the music streaming service is important for me.	
	P3	It is important for me to be able to create customised 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 and Huang, 2011) (Borja et al., 2015) (Borja and Dieringer, 2016; Borja et al., 2015) (Liao and Hsieh, 2013)
	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.	
	AP4*	I do not believe that there is a high risk of getting caught in the practice of piracy.	
	AP5*	I do not believe that the consequences will be very severe if I get caught.	
	AP6*	Downloads do not harm artists because they are already too successful.	
	AP7*	I have a positive perception towards illegal downloads.	
Behavioural 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.	
Behavioural intention to recommend (R)	R1	Usually I recommend using paid music streaming services.	(Johnson et al., 2006) (Hoehle and Venkatesh, 2015; Johnson et al., 2006)
	R2	I would recommend paid streaming music services to someone who seeks my advice	

*: Removed items.

Data was used to test and analyse both the measurement and structural model. Four hundred and thirty-nine anonymous and anonimous responses were collected, and 324 of these proved to be valid for this study's purpose. The final sample is gender-balanced, with a slightly higher number of female respondents (50.9%). It presents an age distribution ranging from under 18–64 years old, the majority being in the age group of 18–34 years (83%). Regarding education, more than 77% of the elements hold a tertiary qualification.

5. Results

5.1. Qualitative results

As far as the 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 fewer CDs are purchased, this is a viable way to* support *their work"*. The main advantages premium users find are the variety of songs and podcasts available in the service, the high quality, information regarding bands/musicians, the value for money, the possibility of creating personalised playlists, suggestions for 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 to 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

Table 2. 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	Elementary	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

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 for new music is fascinating, and it works quite well. Offline access should also 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 affordable prices 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 remarked that: *"A music CD costs €20, as a rule. I don't think Spotify's values are inadequate. If it were 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 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 his favourite band/songs. In this sample, the main ways for respondents to listen to music is through the streaming service Spotify and YouTube due to the ease of access. One person mentioned Apple Music, and two other people mentioned 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 one 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 listen to full concerts when they are only on this platform, published by the artist"*.

The number of people who currently engage in illegal downloads over the internet has visibly decreased as only five members continue performing this illicit act. In the sample, three elements have never done an illegal download. The rest admitted to having already done it frequently; however, they stopped doing it because more ethical ways have appeared that allow listening to music for free or because presently, they have a premium account on a music streaming service. Four elements admitted they still download some songs, rarely. Everyone except two members agreed that these services could completely combat piracy in this industry. Most said 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 activity is seen as nonexistent by the majority, and many of the interviewees did not know what the consequences of this act are. Three participants agreed that there is a risk, but only if done on a large scale.

5.2. Quantitative results

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 and around 77% have a level of education at the 'College' level (77.1%). Furthermore, the majority lies in the age group of 18–34 years (83%). Detailed descriptive statistics on the respondents' characteristics are shown in Table 2.

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 et al., 2015). SEM combines two techniques: covariance-based (as represented by LISREL) and variance-based, in which partial least squares (PLS) path modelling is the most prominent representative (Henseler et al., 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).

5.2.1. 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 can generally be interpreted in the same way (Hair et al., 2014; Henseler et al., 2009). As shown in Table 3, both measures show values very close to or larger than 0.7 for all constructs, satisfying all requirements and thus, admitting construct reliability. The indicator reliability was evaluated through loading values. We used the recommendation of retaining indicators with standardised loading larger than 0.7 (Churchill, 1979; Hair et al., 2014; Henseler et al., 2009). The items FC4, PF4, P5, P6, AP4, AP5 and AP6 (Table 1) were dropped due to the low factor loading. We kept AP3 (0.611) and II3 (0.628) to prevent the construct from only being represented by two indicators.

Firstly common method bias was assessed by running Harman's single-factor test (Podsakoff et al., 2003). The application of exploratory factor analysis with an unrotated solution revealed that the first factor explained 35.72% of the variance, which is under the cutoff value of 50% (Podsakoff et al., 2003). In complement, full collinearity tests were also performed by creating a dummy variable with random values and pointing all the exogenous latent variables in the model to it. The values of variance inflation factors (VIF) were below 3.3 for all latent variables, which also tends to support a model free of common method bias (Kock, 2015).

The average variance extracted (AVE) is used to assess convergent validity (Fornell and Larcker, 1981), it 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

Table 3. 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
Personalisation (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

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 3, all constructs present values higher than 0.5.

Fornell and Larcker (1981) and cross-loadings criteria were used to assess discriminant validity. The Fornell-Larcker criterion (Fornell and Larcker, 1981) allows evaluating discriminant validity on the construct level, and the cross-loadings criteria evaluate it on the indicator level (Henseler et al., 2009). The Fornell-Larcker criterion consists of comparing the square root of the 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. This criterion is met (all diagonal values are greater than the off-diagonal values), as shown in Table 4. Regarding the 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 (Table 5).

The measurement model results assure construct reliability, indicator reliability, convergent validity and discriminant validity of the constructs.

5.2.2. *Structural model*

Once we have assumed that the construct measures are reliable and valid, the next step is assessing the structural results (Hair et al., 2014). First, we started to assess collinearity using the inner variance inflation

Table 4. 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** - personalisation; **AP** - attitude towards piracy; **BI** - behavioural intention; **R** - behavioural intention to recommend.

factor (VIF). All variables showed VIFs smaller than 2, confirming the absence of collinearity problems. Next, the path significances were estimated using the bootstrapping technique, generating 5,000 bootstrap samples (Henseler et al., 2009). The results are shown in Figure 3 and Table 6.

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 service and 69% of behavioural intention to recommend its adoption. Hence, the model can predict the substantive variation of the endogenous variables.

Analysing the path coefficients, we observed the following results. Performance expectancy ($\widehat{\beta} = 0.218$, $p < 0.05$), effort expectancy ($\widehat{\beta} = 0.073$,$p < 0.10$), hedonic motivation ($\widehat{\beta}= 0.090$,$p< 0.10$), price value ($\widehat{\beta}= 0.216$, $p < 0.05$), habit ($\widehat{\beta} = 0.357$, $p < 0.05$), perceived freemium-premium fit ($\widehat{\beta} =$ -0.113,$p < 0.05$) and attitude towards piracy ($\widehat{\beta}= 0.109$, $p < 0.05$) were statistically significant in explaining behavioural intention. This model also confirms the hypothesis that behavioural intention ($\widehat{\beta}= 0.776$, $p < 0.05$) and personalisation ($\widehat{\beta}= 0.112$, $p < 0.05$) 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 empirical results. Social influence and facilitating conditions (both UTAUT2 original constructs), as well as, involvement and interest and personalisation (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 tributary from the original UTAUT2 theory, while hypotheses H8 to H12 relate to the new proposed constructs.

6. Discussion

Since the music industry has gone through changes in all its areas of operation, streaming has become the most popular way to listen to music. Therefore, in order to help fill a research gap, the main goal of this study was to shed light on the music streaming services adoption and recommendation process, analysing users' purchase and recommendation intention of a paid version of these services and testing the applicability of a comprehensive adoption model in this context, extending the original UTAUT2 model.

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. Furthermore, behavioural intention to recommend the use of these paid services is confirmed to be explained by personalisation and the intention to buy.

Regarding the endogenous variable behavioural intention, habit, performance expectancy, and price value were the most important determinants, aligned with Venkatesh et al.'s (2012) findings. However, between them, "habit" revealed to be the strongest determinant ($\widehat{\beta} = 0.357$, $p = 0.000$). This finding may arise from the fact that digitalisation has profoundly revolutionised music consumption by allowing it anytime and everywhere, which was not possible in the past (Cockrill et al., 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 et al., 2015; Nikou and 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 because that habit was created (Ye et al., 2004). Hence, it would be important for music streaming services to develop marketing strategies where the desire to use a paid version would be incited to users in order to create intention and then reflect on effective use.

"Performance expectancy" was accepted as one of the strongest determinants of behavioural intention ($\widehat{\beta} = 0.218$, $p = 0.000$), also 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 consumers are cognizant of the benefits extracted from the use of these services more 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 into 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 experience in the IS field is growing, and thus, it could be helpful for these services, enhancing their utilitarian character, in order to please the consumer more and generate differentiation between competitors. In this context, the performance expectancy can be raised by improving tools to look for music, sorting algorithms, or simplifying sharing in other platforms (Hampton-Sosa, 2017). The process of discovering new music is indispensable to users (Dias et al., 2017;

Table 5. 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**

Loadings in bold.

Hampton-Sosa, 2019; Kjus, 2016); hence, music streaming services should invest in research to discover or improve those kinds of functions. According to Hampton-Sosa (2019), a music streaming service's perceived usefulness can be interpreted as a decrease in piracy.

Concerning "price value", it was also shown that it plays an essential part in the behavioural intention explanation ($\widehat{\beta} = 0.216$, $p = 0.000$). 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 technology are perceived to be greater than the monetary cost and, therefore, price value impacts positively on intention. That is, if 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 with 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 and Goedertier (2016) stated that the price impacts a consumer's decision 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 the intention to adopt a technology by several studies. Thus, researchers and music streaming services should be aware of its utter importance in the adoption decision field, taking it seriously and carefully as a powerful determinant (Chu and Lu, 2007). According to Chu and Lu (2007), pricing strategies are undoubtedly

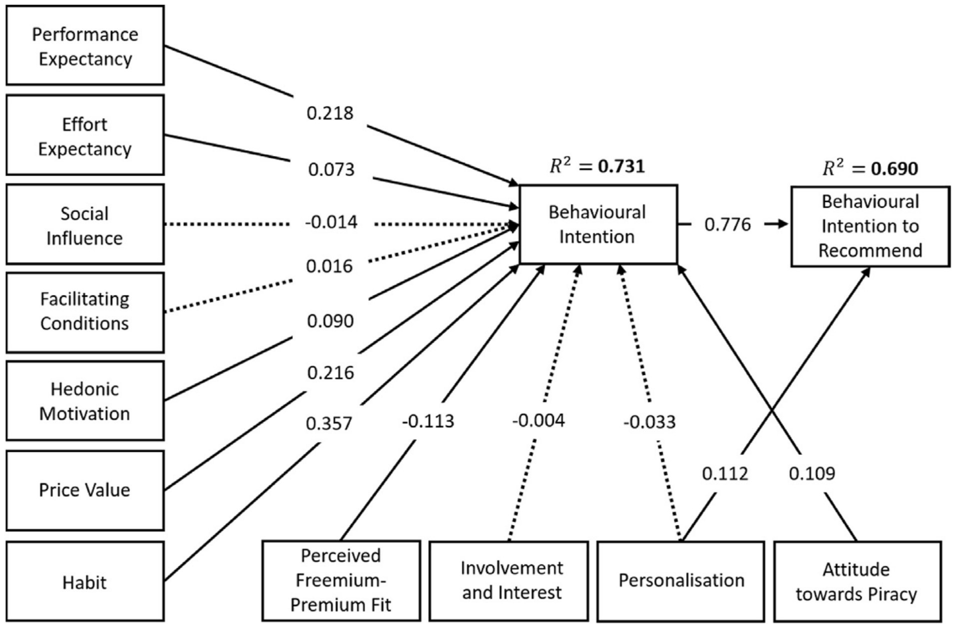

Figure 3. Structural model results. Note: Paths coefficients that are not statistically significant are in dashed arrows.

Table 6. 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	Personalisation → BI	+	-0.033	0.874	No
H10b	Personalisation → 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: * $p < 0.05$, ** $p < 0.10$.
Supported hypotheses in bold.

fundamental for these services in order to offer consumers realistic prices. As price value involves a trade-off between perceived sacrifices versus perceived benefits (Li and Cheng, 2014), it is crucial to understand what is taken into account by music streaming services users and from there, identify and segment the customers, always responding to market changes (Chu and Lu, 2007).

Another determinant of behavioural intention is "hedonic motivation" ($\widehat{\beta} = 0.090$, $p = 0.073$), considering as a significant level, $\alpha = 10\%$. This result is in line with the findings of van der Heijden (2004), Chu and 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 consumer's enjoyment (Hampton-Sosa, 2019). The offer of tools that can bring joy, such as discovering new music through the recommendation options, creating new playlists, or reading artists' information, can all be fun to the consumer (Hampton-Sosa, 2019). Therefore, listening to music can be enjoyable, so it is considered hedonic consumption (Chu and Lu, 2007). Despite the importance of hedonic motivation, performance expectancy is a stronger determinant of intention in this study, contradicting van der Heijden (2004). However, according to Venkatesh et al. (2012), both utilitarian and hedonic benefits are significant drivers of technology use in a consumer context. In order to conquer music consumers, music streaming providers should keep in practice some strategies such as free-trial programs, to enhance their playfulness to potential subscribers (Chu and Lu, 2007) and emphasising the existence of pleasurable and emotional features. For example, Spotify launches Spotify Wrapped at the end of each year, consisting 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 aspect is the fruit of increased investments in data-driven innovation to boost users engagement (Ramos and 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 ($\widehat{\beta}$ = 0.073, p = 0.058), considering as 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 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 and Park (2008) stated that the easier the service is to use, the more confident the consumer would 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 facilitating the payment process, always assuring its security (Oliveira et al., 2016). The importance of effort expectancy was notable in the interviews, where the participants referred to easy access as a perk of music streaming services use.

Two constructs from the UTAUT2 model were found not to have significant impacts on the intention to buy. These are facilitating conditions and social influence. Although the "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, in fact, no statistical significance and, therefore, has not been confirmed ($\widehat{\beta}$ = 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 and Park, 2008). Apparently, if consumers have the required resources to adopt new technology, they will have a stronger intention to use them (Hew et al., 2015). However, our results suggest that consumers do not consider such aspects when pondering acquiring a paid streaming music account. Perhaps this could be due to the generalised level of availability of technologies that allow music streaming services and the easy-to-use factor that makes the technological barriers almost irrelevant. Also, 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 ($\widehat{\beta}$ = -0.014, p = 0.709), contradicting Venkatesh et al. (2012) and Chen et al.'s (2018b) findings. According to Venkatesh et al. (2003), the role of this construct in technology adoption is under unpredictable influences, becoming a complex topic and an interesting matter of study. A possible justification of this result may be related to the fact that this construct seems to be primarily relevant in the early stages of individual experience (Venkatesh et al., 2003). Our data includes information from already existing music streaming users. So, due to the high level of experience in dealing with these services, it may not be surprising that their peers' opinion has not been considered important to the explanation of intention to purchase a paid account. Another possible justification is related to the environment. Venkatesh et al.'s (2003) study claimed that in mandatory environments such as organisational settings, social influence tends to impact behaviour more than in contexts perceived as voluntary. The decision to acquire a paid music account can be seen as a voluntary action. Hence due to this characteristic, the impact of social influence is mitigated. An additional explanation could be the fact that performance expectancy was the second most important predictor of behavioural intention (after habit) (Chipeva et al., 2018), enhancing the weight that consumers give to the utilitarian character of this technology and less importance to the external factors. Finally, in the same line of thought, the hedonic character of these services should be stressed, revealed in the intrinsic use by each consumer and, therefore, less permeable to exterior influences.

Regarding the new proposed constructs and starting with "perceived freemium-premium fit", its impact was verified in the behavioural intention ($\widehat{\beta}$ = -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, users more sensitive to restrictions or differences will be more inclined to acquire a paid version of a music streaming service (Wlömert and Papies, 2016). Our result is of absolute importance to the purchase decision since 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 strategy could become fundamental to raising positive opinions concerning the paid service and thus increase the willingness to pay for them. However, this could be a risky strategy, so it is crucial to define a limit for the usufruct of all the premium features (Wagner and 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 and Hess, 2013). Wagner et al. (2013) suggested that providers should create higher value for paid versions (Wagner et al., 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 maximise the freemium-premium fit or the offer of a limited free trial with all premium features?

As for ''personalisation'', it is observed that it significantly impacts the behavioural intention to recommend ($\widehat{\beta}$ = 0.112, p = 0.003) but not the intention to use. This result is in line with the findings of Ball et al. (2006) and Coelho and Henseler (2012), promoting the importance of service personalisation in the explanation of the willingness to recommend paid music streaming services. Given this fact, we advise music streaming providers to test personalisation 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 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 ($\widehat{\beta}$ = 0.109, p = 0.001), meeting the results of Cesareo and Pastore (2014). An unfavourable perception of piracy positively influences the intention to purchase a paid streaming music service. 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. Considering the growing numbers of paid music streaming revenues, we can assume that users are not interested 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 and Dieringer, 2016), it is important to spread education among 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 and Pastore, 2014). Cesareo and Pastore (2014) recommend that music companies should intensify consumer knowledge by starting marketing campaigns about their legal offers.

Surprisingly, the "involvement and interest" hypothesis was not proved to be relevant in the explanation of behavioural intention ($\widehat{\beta}$ = -0.004, p = 0.892), in contradiction with Cesareo and Pastore's (2014) results. Our questionnaire has revealed strong levels of music interest (mean = 6.10, median = 7), even though we found that it is not relevant for consumers' intention to pay for a music streaming service. One possible justification could be the fact that people that have a higher involvement with music derive satisfaction from its consumption; then, this construct could have been confused with hedonic motivation. This result matches the "personalisation" outcome, which was not found to be relevant for the explanation of behavioural intention ($\widehat{\beta}$ = -0.033, p = 0.382), being in line with Doerr et al.'s (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 make these constructs become explanatory variables of the purchase act of a music streaming service (music as a service). Despite this finding, the customisation topic needs a lot more research (Liang et al., 2006) because consumer interests are constantly evolving and, thus, should be followed for effective personalisation to take place (Anand and Mobasher, 2007).

Last but not least, behavioural intention to purchase paid music streaming services positively influences the intention to recommend them ($\widehat{\beta}$ = 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 communication methods. This aspect could suggest that consumers who have the intention to purchase a paid music streaming account will be more predisposed 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 that 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.

Future research may include adapting this study to other locations and submitting it to a larger number of participants to assure the generalisation 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 freemium users in order to understand which factors weigh more for each one and implement different possible marketing strategies. The addition of new constructs to the present model would be helpful to try to increase the predictive power of our framework. Meanwhile, it might be interesting to deeply explore the effect of paid music streaming services in the abolition of music piracy, namely to verify if this tendency of decrease remains. Intention to recommend should be better explored in this context as its effect is not yet well known in technology acceptance.

8. Conclusions and implications

This study sought to analyse which factors influence the intention to purchase a music streaming service and, consequently, its recommendation. To this end, several hypotheses were tested using an innovative research model, which is an extension of UTAUT2. By analysing our results, it is possible to retain some fundamental insights that could be pertinent for music streaming services providers to perceive the adoption and recommendation process of users.

Regarding the theoretical implications, this study highlights two main aspects. In terms of the determinants of adoption for paid music streaming services, our findings suggest that several but not all of the original constructs of the UTAUT2 model are important determinants of music consumption behaviour. The exceptions are facilitating conditions and social influence, for reasons previously discussed. It also showed that new constructs specific to the music context have to be considered when explaining adoption intentions. These are the perceived freemium-premium fit and the attitude towards piracy. Without contemplating these two factors, conclusions about adoption determinants would present a lack of predictability and generate wrong or less optimal business strategies.

The second research goal was related to the recommendation of such services. Understanding this recommendation intention is of great business value and may be used by companies as a means of inducing further adoption. The main conclusion was that in this industry, behavioural intention is itself a strong driver of the recommendation and consequently that all the direct determinants of the intention to use are themselves significant indirect determinants of the recommendation. Additionally, results elucidated a relevant new finding associated with the significant direct effect of personalisation over the intention to recommend.

The contribution of this research may be useful to the scientific community and technology developers in bringing valuable knowledge to the design of music streaming services regarding user's expectations and preferences (Nikou and Bouwman, 2014).

Concerning the practical implications, one crucial finding of this study is that habit plays the most critical role in influencing the intention to use a paid music streaming service. Other relevant determinants of behaviour intention are performance expectancy, price value, perceived freemium-premium fit, attitude towards piracy, hedonic motivation and effort expectancy, in order of importance. Involvement and interest, and personalisation have not revealed to be salient in users' decision to acquire a paid account of a music streaming service. These conclusions may be used in the design of business strategies aiming to promote users from free to paid services, as companies will be able to understand the expected impact on adoption resulting from manipulating a mix of these drivers.

The findings related to the antecedents of recommendation also seem to be of relevant business value. Understanding that, in this industry, the intention to use is itself a strong driver of recommendation along with the new knowledge about the relevant direct effect of personalisation may contribute to designing business strategies aiming to improve recommendation. In particular, these business strategies may use the knowledge that for the same level of intention to use, it is possible to strengthen recommendation through the personalisation perception. Designing these strategies seems to be particularly useful and promising in the context of social networks.

To conclude, we can state that the adoption intention in the world of music streaming is a complex, multidimensional context. Adoption models designed for traditional information systems adoption still appear to fit this framework partially, but new dimensions have emerged as relevant to explain behavioural intention in this new milieu. 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, make it repetitive, and invest in research about the relevant constructs. In this way, it will be possible to increase the number of recommendations on social networks or by word-of-mouth, helping the acceptance and recognition of these paid services.

Declarations

Author contribution statement

Mariana Lopes Barata, Pedro Simões Coelho: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

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