PressAcademia
www.pressacademia.org/journals/rjbm
RJBM
ISSN 2148-6689
Research Journal of Business and Management YEAR 2023 VOLUME 10 ISSUE 4

MUSIC STREAMING SERVICES AND THE DRIVERS OF CUSTOMER PURCHASE

DOI: 10.17261/Pressacademia.2023.1836
RJBM- V.10-ISS.4-2023(6)-p.195-206

Mariana Lopes Barata[1], José Monteiro Barata[2]
[1]Independent Consultant, Lisbon, Portugal.
mariana_lba@hotmail.com , ORCID: 0009-0003-9773-419X
[2]University of Lisbon, Lisbon School of Economics and Management, Lisbon, Portugal.
jmbarata@iseg.ulisboa.pt , ORCID: 0000-0002-2953-6875

Date Received: August 2, 2023 **Date Accepted:** November 5, 2023

To cite this document
Barata, M.L., Barata, J.M., (2023). Music streaming services and the drivers of customer purchase. Research Journal of Business and Management (RJBM), 10(4), 195-206.
Permemant link to this document: http://doi.org/10.17261/Pressacademia.2023.1836

ABSTRACT

Purpose- 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. This study aims to understand the factors that influence music consumption through streaming platforms, particularly analysing the differences between premium and freemium users on the intention to adopt premium (paid) versions of a music streaming service.

Methodology- UTAUT2 model (version of the Unified Theory of Acceptance and Use of Technology, applied to the consumer side) was used as framework. Based on data collected from 324 music streaming services users (premium and freemium), this study was tested using structural equation modelling (SEM).

Findings- Our findings, focused fundamentally on the initial period of pandemics (2020-2021), confirm that facilitating conditions, price value and performance expectancy play the most important role in influencing the intention to use a paid music streaming service for the premium sample. However, the freemium sample finds habit, price value and hedonic motivation the variables most relevant.

Conclusion- The research contributes insights into music streaming services consumer behaviour, providing several theoretical and practical implications to music streaming services providers.

Keywords: Adoption, customer purchase, music streaming services, SEM, UTAUT2
JEL Codes: M31, M37, C88, L82

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 structure, 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 particular, the growth of streaming services has revolutionised consuming music (IFPI, 2020). It is known that since 2010., for instance, the number of users of the Spotify streaming platform has increased from 15 to 100 million worldwide (Aguiar & Waldfogel, 2018). Spotify currently (2023) has 356 million users.

These platforms are based on a relatively recent business model (Sinclair & 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), 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, increasing the probability of many upgrading to a premium account, where there are several advantages like no advertising, better sound quality and the possibility of offline access (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).

As already said, given the importance of music in all cultures and considering the millions of users of music streaming services, it is imperative to know more about this digital phenomenon and which factors influence their use. There is little research on the willingness to pay for services when a 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). 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 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. 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 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 suggestion of the research model and hypotheses development. Next, we provide the research methodology, data analysis and discussion of results. We conclude with some directions for future work.

2.THEORETICAL BACKGROUND

2.1. Music Streaming Services

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 & 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.

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 & Ajzen, 1975), being used as a basis for many other adoption theories about consumer behaviour. 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.

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. Also, the Technology Acceptance Model (TAM) (Davis, 1989) is one of the most important models in the context of technology adoption and use (Cheong & Park, 2005), based on TRA. Some derivations of this model, like TAM2, have also been proposed (Venkatesh & Bala, 2008; Y.-S. Wang, 2008).

In 2003, Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT), 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, 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. It is a robust theory. Generally, these models can provide a detailed understanding of the phenomena under investigation and a result of successive applications and adaptations. Specifically, the major advantage of the model is that it has included the demographic and experience as factor in the model itself. This makes it more suitable to be used for service-oriented research in business to consumer field. For instance, the traditional TAM models were more often used to adoption of technologies (computers, IT).

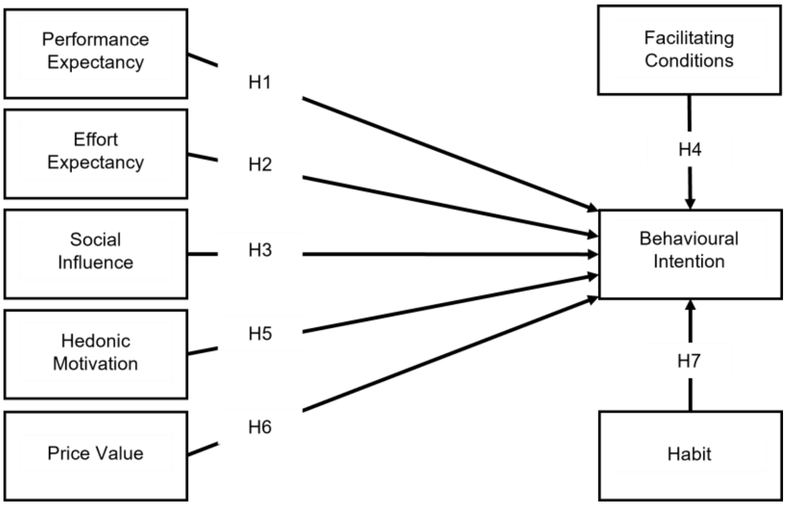
In the following section, we will describe UTAUT2 and its relevance. After UTAUT's release, the model was tested in different contexts and in 2012, it was extended to the consumer context, developing UTAUT2 (Venkatesh et al., 2012). UTAUT2 is an extension of the original model, adding three new constructs: hedonic motivation, price value and habit. Age, gender and experience were considered moderators of behavioural intention and technology use (Venkatesh et al., 2012).

3. RESEARCH MODEL AND HYPOTHESES

3.1. The Model

The model tested in this study is the theoretical UTAUT2 model. The conceptual model is shown in Figure1.

Figure 1: Results Model



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.

3.2. UTAUT2 Variables

Performance expectancy - Performance expectancy is defined as the degree to which using technology will benefit consumers in performing certain activities (Venkatesh et al., 2012). Although online music services aim to deliver an entertaining experience, they also provide functional benefits to people (Chu & Lu, 2007). 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). Hence, we formulate the following hypothesis: **H1,** Performance expectancy (PE) is positively related to behavioural intention (BI).

Effort expectancy - Effort expectancy is described as the degree of ease associated with consumers' use of technology (Venkatesh et al., 2012). According to Kwong & Park (2008), perceived ease of use is a significant predictor of intention. 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. 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 a certain behaviour or not (Ajzen, 1991; Fishbein & Ajzen, 1975). Therefore, we hypothesise: **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 designed to remove barriers to use (Venkatesh et al., 2003). Therefore, we hypothesise: **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, 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). 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).

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). 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. Therefore, we hypothesise: **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; S. Kim & Malhotra, 2005), impacting behavioural intention (Venkatesh, 2000). 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. Therefore, we hypothesise: **H7,** Habit (H) is positively related to behavioural intention (BI).

4. RESEARCH METHODOLOGY

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. See Annex for identification of the measurement scale (items, dimensions and source).

The instrument 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. Thus, the sampling process used in this study was non-probabilistic (Iacobucci & 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.

Data was used to test and analyse both the measurement and structural model. Four hundred and thirty-nine anonymous and confidential 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 to 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

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%).

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).

5.1. 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 considers that indicators have different loadings) and Cronbach's alpha (estimator based on the indicator intercorrelations), which can generally be interpreted in the same way. As shown in Table 1 (premium model) and in Table 2 (freemium model), 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 average variance extracted (AVE) is used to assess convergent validity, it being defined as the mean value of the squared loadings of the indicators associated with the construct. 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 1, all constructs present values higher than 0.5.

Table 1: Premium's Quality Criteria and Factor Loadings

Constructs	AVE	Composite reliability	Cronbach's alpha	Item	Loadings	t-value
Performance Expectancy (PE)	0.575	0.802	0.642	PE1	0.815	21.647
				PE2	0.687	9.403
				PE3	0.768	12.941
Effort Expectancy (EE)	0.740	0.919	0.883	EE1	0.840	12.456
				EE2	0.883	37.786
				EE3	0.918	36.565
				EE4	0.794	14.414
Social Influence (SI)	0.854	0.946	0.915	SI1	0.903	21.085
				SI2	0.913	20.105
				SI3	0.956	33.398
Facilitating Conditions (FC)	0.632	0.837	0.718	FC1	0.852	28.758
				FC2	0.750	10.373
				FC3	0.780	12.143
Hedonic Motivation (HM)	0.647	0.845	0.723	HM1	0.815	17.292
				HM2	0.678	10.051
				HM3	0.905	50.301
Price Value (PV)	0.897	0.963	0.943	PV1	0.936	50.673
				PV2	0.951	81.623
				PV3	0.955	97.357
Habit (HT)	0.642	0.843	0.733	HT1	0.801	12.631
				HT2	0.807	12.727
				HT3	0.795	10.768
Behavioural intention (BI)	0.840	0.940	0.904	BI1	0.942	72.292
				BI2	0.864	24.996
				BI3	0.940	56.952

Table 2: Freemium's Quality Criteria and Factor Loadings

Constructs	AVE	Composite reliability	Cronbach's alpha	Item	Loadings	t-value
Performance Expectancy (PE)	0.688	0.868	0.773	PE1	0.882	45.317
				PE2	0.763	16.286
				PE3	0.839	23.797
Effort Expectancy (EE)	0.758	0.926	0.895	EE1	0.868	12.498
				EE2	0.913	21.242
				EE3	0.916	18.537
				EE4	0.777	8.347
Social Influence (SI)	0.841	0.941	0.906	SI1	0.909	47.225
				SI2	0.920	47.059
				SI3	0.923	48.098

Facilitating Conditions (FC)	0.686	0.867	0.774	FC1 FC2 FC3	0.801 0.836 0.847	7.080 6.636 7.614
Hedonic Motivation (HM)	0.808	0.927	0.882	HM1 HM2 HM3	0.898 0.900 0.898	47.841 60.737 33.765
Price Value (PV)	0.916	0.970	0.954	PV1 PV2 PV3	0.961 0.961 0.949	137.216 134.997 111.411
Habit (HT)	0.828	0.935	0.896	HT1 HT2 HT3	0.882 0.926 0.921	43.823 52.971 64.521
Behavioural intention (BI)	0.838	0.939	0.903	BI1 BI2 BI3	0.921 0.918 0.907	51.930 49.362 50.142

Fornell & Larcker (1981) and cross-loadings criteria were used to assess discriminant validity. This criterion is met (all diagonal values are greater than the off-diagonal values), as shown in Table 3 (premium model) and Table 4 (freemium model).

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

Table 3: Premium's Square Root of AVE (in bold on diagonal) and Factor Correlation Coefficients

Const.	PE	EE	SI	FC	HM	PV	HT	BI
PE	0.758							
EE	0.295	.860						
SI	0.338	0.105	0.924					
FC	0.323	0.514	0.107	0.795				
HM	0.507	0.383	0.337	0.318	0.805			
PV	0.464	0.239	0.274	0.392	0.459	0.947		
HT	0.457	0.226	0.250	0.236	0.383	0.229	0.801	
BI	0.517	0.427	0.222	0.561	0.511	0.539	0.366	0.916

Table 4: Freemium's Square Root of AVE (in bold on diagonal) and Factor Correlation Coefficients

Const.	PE	EE	SI	FC	HM	PV	HT	BI
PE	0.829							
EE	0.249	0.871						
SI	0.438	0.194	0.917					
FC	0.203	0.559	0.230	0.828				
HM	0.467	0.446	0.350	0.344	0.899			
PV	0.466	0.175	0.401	0.321	0.387	0.957		
HT	0.446	0.146	0.405	0.197	0.292	0.460	0.910	
BI	0.503	0.221	0.468	0.190	0.502	0.545	0.565	0.915

Note (Table 3 and Table 4): **PE** - performance expectancy; **EE** - effort expectancy; **SI** - social influence; **FC** - facilitating conditions; **HM** - hedonic motivation; **PV** - price value; **HT** - habit; **BI** - behavioural intention

5.2. 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 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 of the premium model are shown in Fig. 2 and Table 5 and the freemium model results are shown in Fig. 3 and Tabel 7.

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 premium model explains 53% of behavioural intention to adopt a paid music streaming service and the freemium model explains 52.5% of the same intention. Hence, both models can predict the substantive (above 50%) variation of the endogenous variables.

Analysing the path coefficients of the premium model, we observed the following results: H1, H4, H5 and H6 are confirmed by the empirical results. Effort expectancy, social influence and habit were not validated, thus, H2, H3 and H7 are not supported by the premium model.

Analysing the path coefficients of the freemium model we observed the following results: H3, H5, H6 and H7 are confirmed by the empirical results. Performance expectancy, effort expectancy and facilitating conditions were not validated, thus, H1, H2 and H4 are not supported by the freemium model.

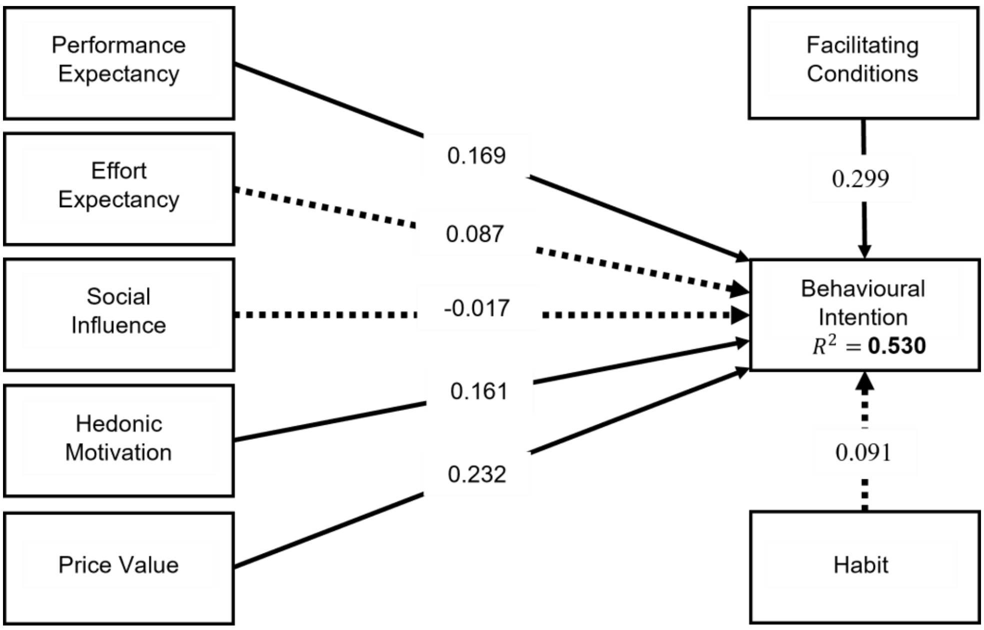
The structural premium model confirms 4 of the 7 hypotheses postulated, as well as the structural freemium model. We can find the differences between models in the Table 7.

Table 5: Premium's Results of the Structural Model and Hypotheses Testing

#	Relationships	Expected sign	Path coeff.	t-value	p-value	Supported
H1	Performance expectancy → BI	+	0.169	2.114	0.035	**Yes***
H2	Effort expectancy → BI	+	0.087	1.214	0.225	No
H3	Social influence → BI	+	-0.017	0.288	0.773	No
H4	Facilitating conditions → BI	+	0.299	3.076	0.002	**Yes***
H5	Hedonic motivation → BI	+	0.161	2.051	0.040	**Yes***
H6	Price value → BI	+	0.232	2.815	0.005	**Yes***
H7	Habit → BI	+	0.091	1.044	0.297	No

Note: * $p < 0.05$

Figure 2: Premium Structural Model Results



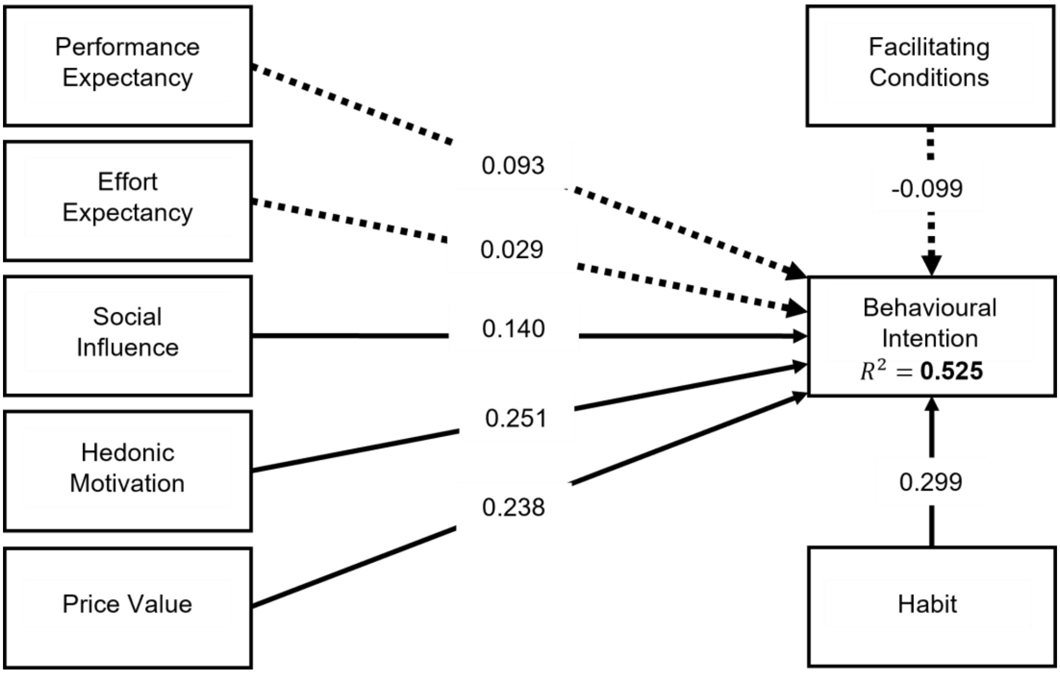
Note: Paths coefficients that are not statistically significant are in dashed arrows.

Table 6: Freemium's Results of the Structural Model and Hypotheses Testing

#	Relationships	Expected sign	Path coeff.	t-value	p-value	Supported
H1	Performance expectancy → BI	+	0.093	1.421	0.155	No
H2	Effort expectancy → BI	+	0.029	0.490	0.624	No
H3	Social influence → BI	+	0.140	1.803	0.071	**Yes****
H4	Facilitating conditions → BI	+	-0.099	1.593	0.111	No
H5	Hedonic motivation → BI	+	0.251	3.457	0.000	**Yes***
H6	Price value → BI	+	0.238	3.135	0.002	**Yes***
H7a	Habit → BI	+	0.299	4.027	0.000	**Yes***

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

Figure 3: Freemium Structural Model Results



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

Table 7: Comparison of Results

#	Relationships	Premium	Freemium
H1	Performance expectancy → BI	Supported*	No
H2	Effort expectancy → BI	No	No
H3	Social influence → BI	No	**No*, Supported****
H4	Facilitating conditions → BI	Supported*	No
H5	Hedonic motivation → BI	Supported*	**Supported***
H6	Price value → BI	Supported*	**Supported***
H7a	Habit → BI	No	**Supported***

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

Additionally, following the paper of Barata & Simões (2021) - reference for this work - , considering specific data and analyzes for Premium and for Freemium, the main results obtained were: i) In the Premium sample, the "performance expectation" influences the purchase intention, in the Freemium it does not; ii) "Social influence" is not taken into account in the Premium sample, however, at a significance level of 10%, in the Freemium sample, its impact is verified; iii) The "access conditions" are taken into account by the Premium sample, not in the Freemium, being the factor that most influences the intention of use in the Premium sample; iv) "Hedonic motivation" and "Price-value" are the only variables that influence both samples, both Premium and Freemium, on the intention to use a paid streaming service; v) The "Habit" influences only the intention of use in the Freemium sample, which is the variable that most influences the intention of use in this sample.

6. DISCUSSION AND IMPLICATIONS

Unsurprisingly, the majority of the 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.

Concerning the **premium model**, it is possible to observe that the variables which explain behavioural intention to buy a premium account are facilitating conditions, price value, performance expectancy and hedonic motivation. ''**Facilitating conditions''** revealed to be the strongest determinant ($\hat{\beta}$ = 0.299, $p = 0.002$) in this model.

"Price value" also shown that it plays an essential part in the behavioural intention explanation ($\hat{\beta}$ = 0.232, $p = 0.005$). 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.

"Performance expectancy" was accepted as one of the determinants of behavioural intention ($\hat{\beta}$ = 0.169 , $p = 0.035$), 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. 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).

Another determinant of behavioural intention is **"hedonic motivation"** ($\hat{\beta}$ = 0.161 , p = 0.040). 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 model, **effort expectancy, social influence and** habit did not impact intention behavioural**.**

Concerning the **freemium model**, it is possible to observe that the variables which explain behavioural intention to buy a premium account are habit, hedonic motivation, price value and social influence. **"Habit"** revealed to be the strongest determinant ($\hat{\beta}$ = 0.299, $p = 0.000$). 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).

Another determinant of behavioural intention is **"hedonic motivation"** ($\hat{\beta}$ = 0.251 , p = 0.000). This finding is in line with the previous result from premium model. This means that price value is taking into account by freemium users as well as premium users.

Concerning **"price value"**, it was also shown that it plays an essential part in the behavioural intention explanation ($\hat{\beta}$ = 0.238, $p = 0.002$). This finding is in line with the previous result from premium model, meaning that price value is taking into account by freemium users as well as premium users. **Social influence** was proved too ($\hat{\beta}$ = 0.140, $p = 0.071$),), considering as significance level, α = 10%. In this model, **performance expectancy, effort expectancy and facilitating conditions** did not impact intention behavioural.

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). 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.

8. CONCLUSIONS

This study sought to analyse which factors influence the intention to purchase a music streaming service, comparing premium and freemium user's results. To this end, several hypotheses were tested using 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 process of users.

Regarding the theoretical implications, 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, depending on the sample.

Concerning the practical implications, we can affirm that in the premium sample, performance expectancy influences adoption, however, in freemium sample, it does not. It is possible to observe that the effort expectancy is not considered by any premium and freemium users when deciding which account to purchase. Social influence is not taken into account in the premium sample, however, at a significance level of 10%, in the freemium sample, its impact is verified in intention to adopt a premium account. Facilitating conditions are taken into account by the premium sample and not by freemium, being the factor that most influences the intention to use in the premium sample. Hedonic motivation and price value are the only variables that influence both samples, premium and freemium, on the intention to use a paid streaming service. Habit only influences the intention in the freemium sample, which is the variable that most impact the intention in this sample.

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.

To conclude, we can state that the adoption intention in the world of music streaming is a complex and 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.

REFERENCES

Aguiar, L., & Waldfogel, J. (2018). As streaming reaches flood stage, does it stimulate or depress music sales? International Journal of Industrial Organization, 57, 278–307. https://doi.org/10.1016/j.ijindorg.2017.06.004

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2002). Residual Effects of Past on Later Behavior: Habituation and Reasoned Action Perspectives. Personality and Social Psychology Review, 6(2), 107–122. https://doi.org/10.1207/S15327957PSPR0602_02

Arditi, D. (2014). ITunes: Breaking barriers and building walls. Popular Music and Society, 37(4), 408–424. https://doi.org/10.1080/03007766.2013.810849

Arditi, D. (2018). Digital subscriptions: the unending consumption of music in the digital era. Popular Music and Society, 41(3), 302–318. https://doi.org/10.1080/03007766.2016.1264101

Barata, M. & Coelho, P. (2021). Music streaming services: understanding the drivers of customer purchase and intention to recommend. Heliyon, 7, 1-17. https://doi.org/10.1016/j.heliyon.2021.e07783

Cesareo, L., & Pastore, A. (2014). Consumers' attitude and behavior towards online music piracy and subscription-based services. Journal of Consumer Marketing, 31(6–7), 515–525. https://doi.org/10.1108/JCM-07-2014-1070

Chen, C. C., Leon, S., & Nakayama, M. (2018a). Are you hooked on paid music streaming? An investigation into the millennial generation. International Journal of E-Business Research, 14(1), 1–20. https://doi.org/10.4018/IJEBR.2018010101

Chen, C. C., Leon, S., & Nakayama, M. (2018b). Converting music streaming free users to paid subscribers: Social influence or hedonic performance. International Journal of Electronic Business, 14(2), 128–145. https://doi.org/10.1504/IJEB.2018.094870

Cheong, J., & Park, M. C. (2005). Mobile internet acceptance in Korea. Internet Research, 15(2), 125–140. https://doi.org/10.1108/10662240510590324

Chu, C., & Lu, H. (2007). Factors influencing online music purchase intention in Taiwan: An empirical study based on the value-intention framework. Internet Research, 17(2), 139–155. https://doi.org/https://doi.org/10.1108/10662240710737004

Churchill, G. A. (1979). A paradigm for developing better measures of marketing constructs. Journal of Marketing Research, 16(1), 64–73. https://doi.org/10.2307/3150876

Cockrill, A., Sullivan, M., & Norbury, H. L. (2011). Music consumption: Lifestyle choice or addiction. Journal of Retailing and Consumer Services, 18(2), 160–166. https://doi.org/10.1016/j.jretconser.2010.12.003

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly: Management Information Systems, 13(3), 319–339. https://doi.org/10.2307/249008

Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of price, brand, and store information on buyers' product evaluations. Journal of Marketing Research, 28(3), 307–319. https://doi.org/https://doi.org/10.2307/3172866

Doerr, J., Benlian, A., Vetter, J., & Hess, T. (2010). Pricing of content services - An empirical investigation of usic as a service. Lecture Notes in Business Information Processing, 58, 13–24. https://doi.org/10.1007/978-3-642-15141-5_2

Dörr, J., Wagner, T. M., Hess, T., & Benlian, A. (2013). Music as a service as an alternative to music piracy? An empirical investigation of the intention to use music streaming services. Business and Information Systems Engineering, 5(6), 383–396. https://doi.org/10.1007/s12599-013-0294-0

Fishbein, M., & Ajzen, I. (1975). Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research. Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-51. https://doi.org/10.2307/3151312

Hair, J. F. Jr., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2014). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM) (2nd ed.). SAGE Publications.

Hampton-Sosa, W. (2017). The impact of creativity and community facilitation on music streaming adoption and digital piracy. Computers in Human Behavior, 69, 444–453. https://doi.org/10.1016/j.chb.2016.11.055

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. Advances in International Marketing, 20(1), 277–319. https://doi.org/10.1108/S1474-7979(2009)0000020014

Iacobucci, D., & Churchill, G. A. (2018). Marketing Research: Methodological Foundations (12th ed., Issue September). CreateSpace Independent Publishing Platform.

IFPI. (2020). Global Music Report 2019. International Federation of the Phonographic Industry (IFPI), 1–44.

Kim, S., & Malhotra, N. (2005). A longitudinal model of continued IS use: An integrative view of four mechanisms underlying postadoption phenomena. Management Science, 51(5), 741–755. https://doi.org/10.1287/mnsc.1040.0326

Kwong, S. W., & Park, J. (2008). Digital music services: Consumer intention and adoption. Service Industries Journal, 28(10), 1463–1481. https://doi.org/10.1080/02642060802250278

Larsen, G., Lawson, R., & Todd, S. (2009). The consumption of music as self-representation in social interaction. Australasian Marketing Journal, 17(1), 16–26. https://doi.org/10.1016/j.ausmj.2009.01.006

Larsen, G., Lawson, R., & Todd, S. (2010). The symbolic consumption of music. Journal of Marketing Management, 26(7–8), 671–685. https://doi.org/10.1080/0267257X.2010.481865

Naranjo-Zolotov, M., Oliveira, T., & Casteleyn, S. (2019). Citizens' intention to use and recommend e-participation: Drawing upon UTAUT and citizen empowerment. Information Technology and People, 32(2), 364–386. https://doi.org/10.1108/ITP-08-2017-0257

Naveed, K., Watanabe, C., & Neittaanmäki, P. (2017). Co-evolution between streaming and live music leads a way to the sustainable growth of music industry – Lessons from the US experiences. Technology in Society, 50, 1–19. https://doi.org/10.1016/j.techsoc.2017.03.005

Oestreicher-singer, G., & Zalmanson, L. (2013). Content or community? A digital business strategy for content providers in the social age. MIS Quarterly: Management Information Systems, 37(2), 591–616. https://doi.org/https://doi.org/10.25300/MISQ/2013/37.2.12

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). SmartPLS 3.

Sinclair, G., & Green, T. (2016). Download or stream? Steal or buy? Developing a typology of today's music consumer. Journal of Consumer Behaviour, 50(October), 35–50. https://doi.org/10.1002/cb.1526

Sinclair, G., & Tinson, J. (2017). Psychological ownership and music streaming consumption. Journal of Business Research, 71(September), 1-9. https://doi.org/10.1016/j.jbusres.2016.10.002

Thomes, T. P. (2013). An economic analysis of online streaming music services. Information Economics and Policy, 25(2), 81–91. https://doi.org/10.1016/j.infoecopol.2013.04.001

van der Heijden. (2004). User acceptance of hedonic information systems. MIS Quarterly, 28(4), 695–704. https://doi.org/10.2307/25148660

Venkatesh, V. (2000). Determinants of perceived ease of use: integrating control, intrinsic motivation, and emotion into the technology acceptance model. Information Systems Research, 11(4), 342–365. https://doi.org/10.1287/isre.11.4.342.11872

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. Decision Sciences, 39(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly: Management Information Systems, 27(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly: Management Information Systems, 36(1), 157–178. https://doi.org/10.2307/41410412

Wagner, T. M., Benlian, A., & Hess, T. (2014). Converting freemium customers from free to premium—the role of the perceived premium fit in the case of music as a service. Electronic Markets, 24(4), 259–268. https://doi.org/10.1007/s12525-014-0168-4

Wang, Y.-S. (2008). Assessing e-commerce systems success: a respecification and validation of the DeLone and McLean model of IS success. 18, 529–557. https://doi.org/10.1111/j.1365-2575.2007.00268.x

Wlömert, N., & Papies, D. (2016). On-demand streaming services and music industry revenues - Insights from Spotify's market entry. International Journal of Research in Marketing, 33(2), 314–327. https://doi.org/10.1016/j.ijresmar.2015.11.002

Ye, L. R., Zhang, Y. J., Nguyen, D.-D., & Chiu, J. (2004). Fee-based Online Services: Exploring Consumers' Willingness to Pay. Journal of International Information Management, 13(2), 133–141.

Zimmer, S. J. (2018). Rise of Music Streaming. Salem Press Encyclopedia.

APPENDIX: CONSTRUCTS, ITEMS AND REFERENCES EMPLOYED

Constructs	Code	Items	References
Performance Expectancy (PE)	PE1 PE2 PE3	I find paid music streaming services useful in my daily life. Using paid music streaming services help me accomplish things more quickly. Using paid music streaming services increase my productivity /performance.	(Venkatesh et al., 2012)
Effort Expectancy (EE)	EE1 EE2 EE3 EE4	Learning how to use paid music streaming services is easy for me. My interaction with paid music streaming services is clear and understandable. I find paid music streaming services easy to use. It is easy for me to become skilful at using paid music streaming services.	(Venkatesh et al., 2012)
Social Influence (SI)	SI1 SI2 SI3	People who are important to me think that I should use paid music streaming services. People who influence my behaviour think that I should use paid music streaming services. People whose opinions that I value prefer that I use paid music streaming services.	(Venkatesh et al., 2012)
Facilitating Conditions (FC)	FC1 FC2 FC3 FC4*	I have the resources necessary to use paid music streaming services. I have the knowledge necessary to use paid music streaming services. A paid music streaming service is compatible with other technologies I use. I can get help from others when I have difficulties using paid music streaming services.	(Venkatesh et al., 2012)
Hedonic Motivation (HM)	HM1 HM2 HM3	Using paid music streaming services is fun Using paid music streaming services is enjoyable. Using paid music streaming services is very entertaining	(Venkatesh et al., 2012)(van der Heijden, 2004)
Price Value (PV)	PV1 PV2 PV3	A paid music streaming service is reasonably priced. A paid music streaming service is a good value for the money. At the current price, a paid music streaming service provides a good value.	(Venkatesh et al., 2012)
Habit (HT)	HT1 HT2 HT3	The use of paid music streaming services has become a habit for me. I am addicted to using paid music streaming services. I must use paid music streaming services.	(Venkatesh et al., 2012)
Behavioural intention (BI)	BI1 BI2 BI3	I intend to continue using paid music streaming services in the future. I will always try to use paid music streaming services in my daily life. I plan to use paid music streaming services in the near future.	(Venkatesh et al., 2012)

*: Removed item