Consumers' Intentions to Subscribe to Music Streaming Services

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Title of thesis Consumers' Intentions to Subscribe to Music Streaming Services

Degree Master's Degree

Degree programme Marketing

Thesis advisor(s) Jukka Luoma and Henrikki Tikkanen

Year of approval 2016   **Number of pages** 50   **Language** English

Abstract

Digitalization has had a tremendous effect on the music industry and consequently the size of the industry has more than halved during the new millennium. The reason for the falling revenues of the industry lies in growing competition with other entertainment industries, digital music piracy, and poor service models that provide much less revenue for the industry as the previously dominant CD format. The industry is currently in transition from physical to digital and consumers need to be directed to use digital services that provide value to the industry. The most advanced and profitable digital service model today is the paid MaaS (Music as a Service) model, also known as subscription-based music streaming. Paid MaaS services are the fastest growing consumption model of music and their growth underpinned the first positive year for the recording industry in nearly two decades. So that the music industry could continue and accelerate its new-found growth, this thesis intends to find out the factors that affect consumers' behavioral intentions to adopt paid MaaS services.

The research framework of this thesis is built from previous information services (IS) adoption literature, using effort expectancy (EE), facilitating conditions (FC), habit (HT), hedonic motivation (HM), perceived usefulness (PU), price value (PV), and social influence (SI) as hypothesized factors affecting consumers' behavioral intentions to use paid MaaS, as well as tangibility preference (TP), which is an extension to previous theories. The results of a survey with 136 participants indicate that HT, HM, and PV act as direct determinants of consumers' behavioral intention to use paid MaaS, explaining 53% of the variance in behavioral intention.

The study has both, managerial and theoretical implications. It suggests that paid MaaS services should focus on providing their users a good price value and hedonic pleasure, while exploiting consumers' tendency for habitual system usage. On a theoretical side, this study sheds light on factors that determine the behavioral intention to use hedonic information systems. It suggests that in a highly hedonic IS system the determinant of PU loses its predictive power over behavioral intention and the importance of HM increases.

Keywords music as a service, UTAUT2, hedonic information services, IS adoption

Aalto-yliopisto, PL 11000, 00076 AALTO
www.aalto.fi
Maisterintutkinnon tutkielman tiivistelmä

**Aalto-yliopisto
Kauppakorkeakoulu**

Tekijä Aapeli Helkkula	
Työn nimi Kuluttajien aikomus käyttää maksullisia musiikin suoratostopalveluita	
Tutkinto Kauppatieteiden Maisteri	
Koulutusohjelma Markkinointi	
Työn ohjaaja(t) Jukka Luoma ja Henrikki Tikkanen	

Hyväksymisvuosi 2016	**Sivumäärä** 50	**Kieli** Englanti	

Tiivistelmä

Digitalisaatiolla on ollut valtaisa vaikutus musiikkiteollisuuteen ja sen johdosta musiikkiteollisuuden koko on supistunut alle puoleen siitä mitä se oli ennen vuosituhannen vaihdetta. Syitä musiikkialan laskevaan liikevaihtoon ovat kasvava kilpailu muiden viihdealojen kanssa, digitaalinen piratismi ja kehnot digitaaliset palvelumallit, jotka tuovat musiikkiteollisuudelle huomattavasti vähemmän tuloja kuin aikaisemmin kulutusta dominoinut CD formaatti. Musiikkiala on tällä hetkellä siirtymävaiheessa fyysisestä digitaaliseen ja kuluttajia tulisi ohjata käyttämään digitaalisia palvelumalleja, jotka tuottavat arvoa musiikkiteollisuudelle. Tällä hetkellä kaikista kehittynein ja tuottoisin digitaalinen palvelumalli on niin sanottu maksullinen MaaS (Music as a Service), eli musiikin suoratoistopalvelun tilaus -malli. Maksulliset MaaS-palvelut ovat nopeiten kasvuva musiikin kulutustapa ja ne ovat vastuussa musiikki alan ensimmäisesta positiivisesta tuloksesta lähes kahteen vuosikymmeneen. Jotta musiikkiala voi jatkaa ja nopeuttaa kasvuaan, tämä Pro Gradu tutkii mitkä tekijät vaikuttavat kuluttajien aikomuksiin käyttää maksullisia MaaS-palveluita.

Tämän tutkielman teoreettinen kehys on rakennettu aikaisemmista informaationpalveluiden käyttöönottoteorioista ja se olettaa, että helppokäyttöisyys, olosuhteet, tottumus, hedoninen motivaatio, oletettu hyödyllisyys, hinta-arvo, sosiaalinen influenssi ja aineellisuus preferenssit vaikuttavat kuluttajien aikomuksiin käyttää maksullisia MaaS palveluja. Tutkimuksen tulokset johdettiin kyselystä, johon vastasi 136 kuluttajaa. Tulosten mukaan tottumus, hedoninen motivaatio ja hinta-arvo vaikuttavat suoraan kuluttajan aikomukseen käyttää maksullista MaaS palvelua. Tutkimuksen teoreettinen malli selitti 53% käyttöaikomusten varianssista.

Tällä tutkimuksella on käytännöllisiä- ja teoreettisia implikaatioita. Se ehdottaa, että maksullisten MaaS-palveluiden tulisi keskittyä tarjoamaan käyttäjilleen hyvä hinta-arvo ja tuottaa hedonista nautintoa, sekä käyttää hyväksi kuluttajien taipumusta tottumukselliseen palvelun käyttöön. Teoreettisella puolella tämä tutkimus valottaa tekijöitä, jotka määrittelevät hedonisten informaatiosysteemeiden käyttöaikomusta. Tutkimus osoittaa, että erittäin hedonisessa informaatiosysteemissä oletettu hyödyllisyys kadottaa määrittävän asemansa käyttöaikomuksiin ja hedonisen motivaation tärkeys kasvaa.

Avainsanat digitaaliset musiikkipalvelut, UTAUT2, hedoniset informaatiopalvelut, informaatiopalveluiden käyttöönotto

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1 INTRODUCTION

Music industry has experienced tremendous changes as a result of digitalization. The distribution and consumption methods of music have changed rapidly and at the moment, the supply is scattered into multiple different forms of physical and digital products. While physical forms of music still exist their share of the industry is in decline and digital is taking over—2014 being the year when digital caught up with physical in terms of revenue. The digital revolution, like the industry calls it, begun after the first successful peer-to-peer file-sharing service Napster launched in 1999. Since then the industry has been on its toes, trying to fight illegal file-sharing from eating its profits and attempting to develop products and services that satisfy the demands of the insistent consumers of today. The power structure of the industry has flipped over and the control has shifted from record labels to the artists and consumers (Graham et al. 2004). Music is also facing more competition than ever before from other sources of entertainment such as the movies, TV, games, and the Internet. The music industry has not been able to keep up with the rapidly evolving business environment that they inhabit and the size of the industry has shrunk from 36.9 billion USD in 2000 (IFPI 2001) to 15 billion USD in 2014 (IFPI 2015). The industry may never grow to be as large as it was in 2000, but in order to turn the decline into a steady rise, they need to find better ways to serve their customers and capture value.

Today, the music industry is in a transition stage. While physical products still exist and they provide a large share of the industry revenue, the consumption is moving away from physical towards the digital, and consequently from ownership of products to access (Wikström 2012). Digitalization has made music—a product that used to be physical—into an intangible information good. This transformation has reshaped the product characteristics of music. Music is an experience good that needs to be heard before it can be evaluated by a consumer (Bhattacharjee et al. 2009). It also has the characteristics of a quasi-public good, meaning that it is difficult to prevent consumers from sharing the good with others, and sharing the good does not decrease its consumption utility (Gopal et al. 2006, Cesareo and Pastore 2014). As an information good, music has a high production cost but the reproduction costs are virtually zero (Bhattacharjee et al. 2003). Because digital music can be copied easily and transferred quickly, it has lost its scarcity. Music can be downloaded for free and with minimal legal risks via illegal file-sharing services or it can be listed to without costs via websites such as YouTube and Soundcloud. To regain its

profitability, the recording industry needs to rebuild scarcity and as it cannot be built around content, it needs to be built around the consumption experience (Mulligan 2015).

The consumption patterns and consumer preferences suggest that the sales of physical products, such as the CD are slowly decreasing and that the future of music consumption is digital. This is a scary situation for the music industry since the CD has been a very profitable product for them and many of the current digital music services provide very little or no revenue for the industry. While in developed markets, such as Sweden, the CD sales today account only for 11% of the market size (IFPI Sverige, 2016), CD is globally still the largest selling music product (Mulligan 2015). The transition from physical to digital is ongoing and the industry needs to manage this transition by directing consumers to use services that bring value to the industry. According to the industry numbers and previous research, subscription-based music streaming services are the best solution to grow the music industry (Small 2012). After almost two decades of falling revenues, the industry saw its first year of growth in 2015, thanks to the rising revenues from streaming services (IFPI 2016). Streaming has in fact been described as "the largest disruptor the industry has seen in a decade" (McIntyre 2014) and as "the last great hope for the recording industry" (Small 2012). This research tries to help the music industry in managing the transition from physical to digital and studies what makes consumers adopt subscription-based music streaming services or in other terms, paid MaaS (Music as a Service) services.

This thesis is structured as follows. First, the different types of online music services are specified. Paid MaaS and its advantages are described more precisely and the research question is presented. Second, the previous literature is discussed, which entails digital piracy and music service adoption, as well as relevant information services (IS) adoption theories. The research model and the hypotheses are presented at the end of the literature review. Then, the methodology of the study is described, followed by data analysis. After that, the data is discussed and conclusions with theoretical and managerial implications are drawn from the discussion, along with limitations of this study and suggestions for further research.

1.1 ONLINE MUSIC SERVICES

Digitalization has opened the doors for new market entrants and the digital music markets have currently more than 400 licensed music services globally (IFPI 2015). To understand

the choices that consumers face when choosing how they consume their music, it is important to understand the characteristics of these different services.

Dörr et al. (2013) distinguishes three different types of online music service models: download-to-own, download-to-rent, and music as a service (MaaS). The first category of Dörr et al. that is the download-to-own model, is also known as the à-la-carte model. In download-to-own a user purchases songs and downloads them into their own hard drive, obtaining the possession as well as the ownership of the music. The best known download-to-own service is Apple's iTunes, which is generally seen as the first successful online music service. Download-to-rent model differs from download-to-own model by not granting the ownership of the music files to the user. The users pay normally a fixed monthly fee, which allows them to download music into their hard drive and granting them the right to use the music. This right expires after the user unsubscribes from the service. An example of the download-to-rent model is the already extinct Nokia Comes with Music. The music files provided by download-to-own and download-to-rent services are often protected by digital rights management (DRM) software, which prevents the files from being copied or listened in other devices. The MaaS model differs from the two other models by not giving possession of the music files to the users. Instead, the service provides users an access to their music library, which means that instead of downloading songs, a user streams the music from the service provider while listening. MaaS services get their revenue either from monthly subscription fees or from advertisements. In addition to the models suggested by Dörr et al., there are music services that do not allow users to search and select the music that they listen to, but where the listening experience is more radio-like and the users are provided pre-selected playlists. An example of this type of a service is Pandora. There are also multiple unlicensed services that are considered illegal as they disrespect the prevailing copyright laws. Despite being illegal, these services are widely used and they do not charge users when downloading music.

1.2 PAID MAAS

This research concentrates on paid MaaS services, because they are demonstrated to provide the most revenue per user when compared to any other online music service. They also represent the newest innovation in the music industry and they are behind the industry's current growth. Paid MaaS services are also known as subscription-based music streaming services (Small 2012), online subscription music services (Wikström 2012), or premium music streaming services (Wlömert and Eggers 2014). To define the term, paid

MaaS service is a licensed music service that provides it users an access to a comprehensive music library via streaming and draws revenues from monthly subscription fees. Many of the MaaS companies also provide a free alternative to paid MaaS. The free alternative (free MaaS) has often limited features compared to those of paid MaaS and it gets revenue from advertisements. The distinction between the two different MaaS services is important as the average revenue per user is a lot higher in paid MaaS and the service features are more advanced. Free MaaS is a so-called freemium service that is used mostly to attract users to adopt the more profitable and advanced paid MaaS model (Dredge 2015).

Before MaaS and streaming, the music distribution channels were mostly based on ownership. However, globalization and the internet have increased the flow of people and information goods tremendously and created what researchers call the liquid modernity (Wikström 2012). In liquid modernity, physical possessions become a burden to the consumers and they prefer access over ownership. This phenomenon is argued to be the reason why access-based distribution channels are taking over the ownership-based channels in music consumption (ibid.). Wikström (2012) also claims that the access-based model will eventually be taken over by a context-based model, where the value of a service is no longer in the music but in the services that are built around it. We can already see the context-based model at function as paid MaaS services are no longer competing with the amount of music in the service but rather with different service features.

1.3 RESEARCH QUESTION

In conclusion, paid MaaS services provide the best average revenue per user for the music industry as well as the most advanced service features for the consumers. They are in a key role in growing the music industry and it is thus important for the industry to direct consumers to use paid MaaS services, instead of other music consumption alternatives. While it is important for the industry to understand the antecedents that lead users to pay for MaaS, it is also vital for the MaaS services themselves, who struggle to convert their freemium users into paid customers (Wagner and Hess 2013). The freemium model is widely used in other industries as well. Hence, the results of this thesis can benefit other industries in addition to the music industry. Despite the importance of the subject, previous research has done very little study on what makes a consumer pay for a service when they can have its basic functionalities for free (Oestereicher-Singer and Zalmanson

2009, Wagner and Hess 2013). The research question of this thesis is: *What factors lead consumers to adopt paid MaaS services?*

2 LITERATURE REVIEW

This chapter reviews the relevant literature for this study. First, the digital piracy of music is discussed along with its effects on the music industry. Second, the previous music services adoption literature is reviewed and relevant theories for this study are reviewed. Third, the development of the research model is discussed and the hypotheses of are presented. Lastly, this chapter presents the research model used for this study with a summary of the hypotheses.

2.1 DIGITAL PIRACY OF MUSIC

Digital piracy is a subject that cannot be left untouched in the context of music consumption and distribution. According to recent studies, 20% of people with fixed-line internet repeatedly use services that infringe music copyrights (IFPI 2015). Many users consume their music through illegal services that violate copyrights and the illegal services make enormous advertising revenues by sharing illegal content.

Music piracy can be divided into two parts: physical piracy and Internet piracy. Physical piracy refers to the distribution and purchasing of illegal, physical copies of music files, while Internet piracy entails illegal downloading, file-sharing, and mobile music piracy (Wang et al. 2009). The purchasing of pirated CDs is decreasing but faster connections and digital compression technologies, as well as the anonymity of the Internet, have dramatically increased the online sharing of music files (Bhattacharjee et al. 2003, Cesareo and Pastore 2014). Because CDs contain music media files, both, the Internet piracy and pirated CDs fall under Cronan and Al-Rafee's (2008) definition of digital piracy: "the illegal copying/downloading of copyrighted software and media files".

The phenomena of digital piracy and rapid digitalization has turned the attention of researchers towards the music industry. It is hard to name any other industries where the products have been acquired illegally in such scale or where digitalization has had as large of an effect to the industry dynamics, as what has been the case in the music industry. Digital piracy has been generally seen as the main reason for the falling revenues of the industry and the industry players have fought digital piracy with lawsuits, anti-piracy software, and DRM software. Just like the industry players, the researchers have also focused on how to take down piracy. Multiple researchers have concentrated their efforts in finding out what drives people to pirate music (e.g. Bhattacharjee et al 2003, Gopal et al. 2004, Cronan and Al-Rafee 2008, Wang et al. 2009). They have found out that age

(Bhattacharjee et al. 2003, Gopal et al. 2004), gender, price of music (Bhattacharjee et al. 2003), internet bandwidth (Kwong and Lee 2002), behavior and opinion of peers (Wang et al. 2009), past piracy behavior, moral obligation, perceived behavioral control, and perceived consequences (Cronan and Al-Rafee 2008) are factors that affect consumers' piracy behavior.

In hopes of turning the plummeting revenues of the music industry back to rise, researchers have suggested different actions to battle digital music piracy. These actions are anti-piracy campaigns (Gopal et al. 2004, Cronan and Al-Rafee 2008, Wang et al. 2009), anti-piracy software, increasing the cost of piracy-related hardware (Cronan and Al-Rafee 2008), changing the product from albums to single tracks (Kwong and Lee 2002), music subscription model (Bhattacharjee et al. 2003), new pricing models, and providing new forms of digital music (Wang et al. 2009). The actions that are trying to impede piracy (e.g. anti-piracy software) or change people's opinions (e.g. anti-piracy campaigns), have had a very limited effect on deterring piracy (Gopal et al. 2004, d'Astous et al. 2005). Bhattacharjee et al. (2006) point out that piracy cannot be defeated by legal means alone, but new business models, pricing strategies, and licensing schema need to be developed. Steve Jobs, the former CEO of Apple, who created the first successful, legal digital music distribution system, the iTunes, said that people do not stop pirating without legal services that offer them benefits over the illegal alternatives (Goodell 2011). Thus, it seems like the answer on how to fight piracy is in shaping the current legal alternatives to become more appropriate with the new digital landscape of music consumption. MaaS is so far the most innovative and successful competitor to illegal music services, which is why this research wants to find out what makes consumers adopt MaaS, more specifically, paid MaaS services.

Even though piracy is generally seen as harming the music industry and the legal sales of music, the research on the subject has been inconsistent. Some studies suggest that digital piracy has brought damage to the music industry and that it has had a negative effect on record sales (e.g. Zentner 2005, Liebowitz 2006, Bender and Wang 2009), while others claim that there is no significant connection between digital piracy and record sales (e.g. Oberholzer-Gee and Strumpf 2007, Wang et al. 2009). Oberholzer-Gee and Strumpf (2007) point out that file-sharing has not had a negative effect on artist creativity either and in fact the amount of new music, e-books, and movies has increased during the time of digital piracy. Some researchers even claim that digital piracy has been beneficial to the

music industry. Piracy has enabled consumers to try out the products before purchasing by lowering the sampling cost, which is found to have a positive impact on intention to purchase (Gopal et al. 2006). Choi and Perez (2007) observed that digital piracy helps businesses by advancing technologies, providing valuable market insight, contributing to new market creation, and spurring the development of innovative legitimate businesses. Regardless of whether digital piracy has actually hurt record sales or not, it is safe to claim that it has had an enormous effect on the industry and that it has stimulated companies to launch new legitimate digital music businesses, such as MaaS.

2.2 PREVIOUS MUSIC SERVICE ADOPTION RESEARCH

Digitalization in the music industry has been extremely fast. It has been so fast in fact that instead of using the term digitalization, the industry is talking about a digital revolution (IFPI 2015). The advent of the digital revolution of the music industry can be pinpointed to the year 1999 when the first ever peer-to-peer music file-sharing service Napster was launched. Since then, consumers have been able to acquire music faster and easier than ever, without the need of physical stores, and they have been able to store music with less effort, without the need of physical discs. Napster and other illegal file-sharing networks led the digital revolution and it took years for companies to develop legal alternatives that were able to compete with the illegal services. Throughout the digitalization process, researchers have studied how to get people to adopt legitimate digital music services. However, as the music services and their business models have varied greatly, many previous studies have quickly become outdated. Moreover, many studies have researched the adoption of illegal music services or the adoption of digital music services in general, and not concentrated on specific, legitimate digital music services such as MaaS. Therefore, more research is needed on consumers' adoption of MaaS and moreover, paid MaaS, which is what this research is set out to do. This chapter reviews the previous research on music service adoption and the theories used.

The adoption of different music services have been studied with a variety of different theoretical models. Digital music services can be categorized as information systems (IS) and the prevalent research stream being used in the adoption of digital music services is the study of IS adoption. The grand theory from which most of the theories in consumer adoption of IS are derived from is the theory of reasoned action (TRA) by Fishbein and Ajzen (1975). TRA originates from the field of psychology and it has been used as a base theory for many user acceptance theories. It is one of the most well-known and validated

research frameworks on consumer behavior to date (Cesareo and Pastore, 2014). The theory proposes that human behavior is the result of intention, which is affected by two determinants *attitude* and *subjective norms*. TRA has been previously used in the context of MaaS by for example Cesareo and Pastore (2014).

Other theories often applied to study the use of new IS services and technologies are the Theory of Planned Behavior (TPB) by Ajzen (1991), the Technology Acceptance Model (TAM) by Davis (1989), and the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2) by Venkatesh et al. (2003, 2012) (Dörr et al. 2013). The theories are reviewed in this chapter. Each of these theories have also been used in the context of music services, but never directly to study the adoption of paid MaaS. Venkatesh et al. (2003) demonstrated the basic concept of user acceptance models where the actual use of information technology is predicted by intentions. The basic concept of user acceptance models is depicted in Figure 1. Fishbein and Ajzen (1975) were the first ones to theorize the strong relationship between individuals' intentions and their actual behavior. Multiple studies since have demonstrated the relationship (e.g. Ajzen 1991, Venkatest et al. 2003, Venkatesh et al. 2012).
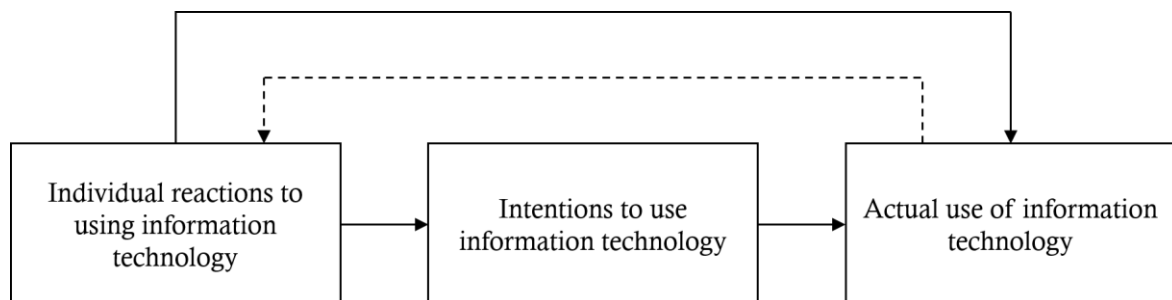
Figure 1. Basic concept underlying user acceptance models. (Venkatesh et al. 2003)

2.2.1 THEORY OF PLANNED BEHAVIOR

Theory of Planned Behavior (TPB) is a social and behavioral sciences theory that predicts and understands human behavior in specified contexts. TPB is depicted in Figure 2. The theory posits that individuals behave rationally and that their behavior is guided by three factors: *attitude*, *subjective norm*, and *perceived behavioral control* (Ajzen 1991). TPB is well-recognized and one of the most used behavioral intention models. One of the benefits of TPB is its flexibility of being extended with other relevant theoretical variables (d'Astous et al. 2005). Due to its characteristics the theory has been the most widely used in the context of music distribution channels (e.g. d'Astous et al. 2005, Plowman and Goode 2009, Dörr et al. 2013, Wagner and Hess 2013). TPB can also be combined with

other streams of theory, such as the TAM, which was what Dörr et al. (2013) did in their study of MaaS adoption by music pirates. TPB has been used in the development of UTAUT2 model and its constructs are similar of those in UTAUT2, which is the theory used as the basis of the research model in this study. The constructs of subjective norm and perceived behavioral control from TPB are used in this research, among other constructs (see. 2.3.8 Social influence and 2.3.3 Facilitating conditions).
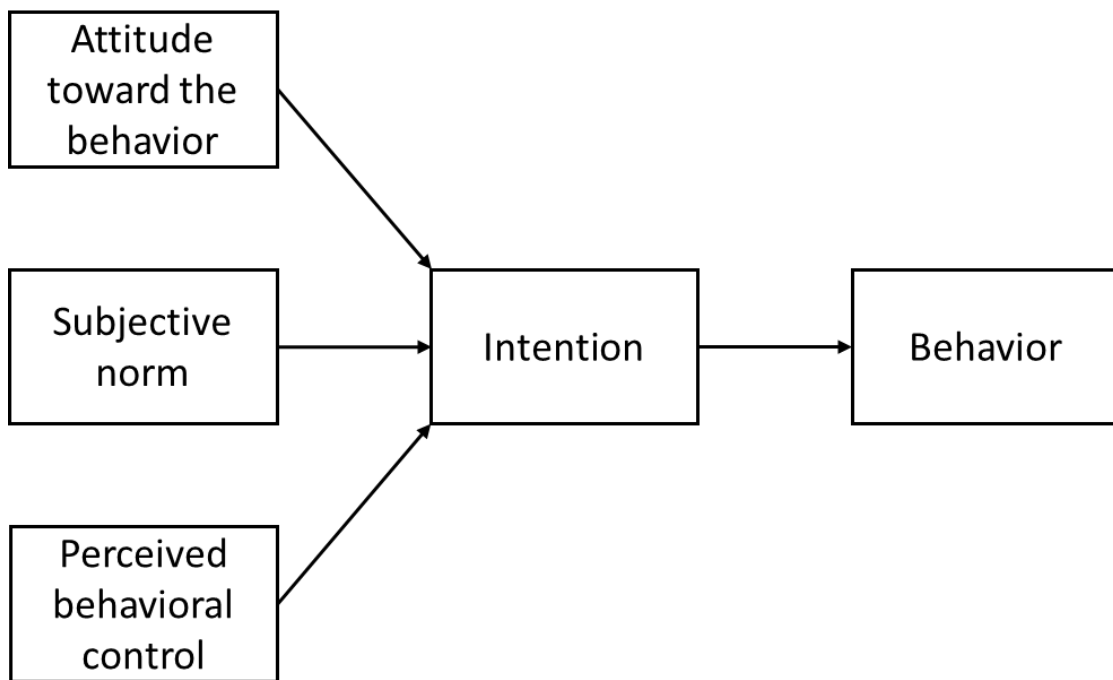
Figure 2. Theory of planned behavior. (Ajzen 1991)

2.2.2 TECHNOLOGY ADOPTION MODEL

Technology Adoption Model (TAM) by Davis (1989) brought in two new theoretical constructs: *perceived usefulness* and *perceived ease of use*, which are both used as constructs in our research model, the latter by the term *effort expectancy*. Both constructs are seen to directly impact the intention to use a technology. Perceived usefulness refers to the extent that an individual believes that using a certain technology will help them better perform a task compared to their performance without the technology (Davis 1989). Perceived ease of use on the other hand, refers to their belief of the effortlessness of the technology. The logic behind perceived ease of use is that even though a person believes that a technology would be useful for them, they might not adopt it if they perceive that using the technology demands too much effort. In TAM, perceived ease of use is also seen to affect perceived usefulness. Venkatesh and Davis (2000) reason that the more effortless a system is to use, the more usefulness can be derived from it. TAM was later extended

with factors of subjective norm, image, job relevance, output quality, result demonstrability, and moderators of experience and voluntariness of use (Venkatesh and Davis 2000). The extended model of TAM is known as TAM2. TAM has been previously used in the context of music services adoption (e.g. Kwong and Park 2008, Dörr et al 2013). The theory is presented in Figure 3.
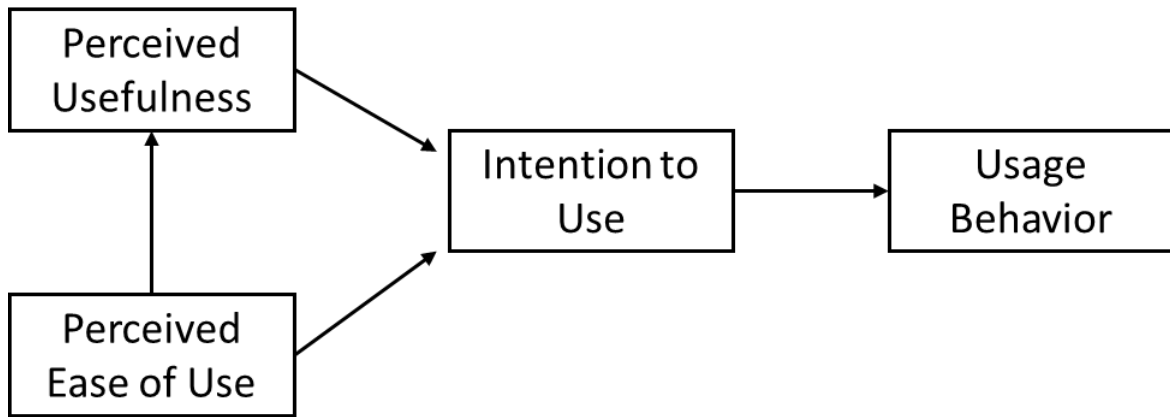
Figure 3. Technology adoption model. (Davis 1989)

2.2.3 UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY—UTAUT AND UTAUT2

This study uses the Unified Theory of Acceptance and Use of Technology—more specifically the UTAUT2—as a basis for the research model. UTAUT2 is an extension to UTAUT, which was developed by Venkatesh et al. (2003). UTAUT2 was chosen over other IS adoption theories due to its versatility, performance, and consumer orientation. UTAUT has been widely used to study the use and adoption of numerous technologies in both organizational and non-organizational contexts (Venkatesh et al. 2012). However, the theory was primarily built to study technology use and adoption in a corporate environment, which led Venkatesh et al. (2012) to develop the UTAUT2—an extension of the previous model, designed to consumer context.

UTAUT

The UTAUT research model was built on previous literature and theoretical models that studied the use and adoption of new information technologies. Venkatesh et al. (2003) compared eight models from previous literature and constructed a unified theory based on the conceptual and empirical similarities of these models. According to their empirical test, the UTAUT model outperforms the eight previous models. The eight models used to formulate the UTAUT model were the previously reviewed TRA, TPB, TAM and TAM2,

as well as Motivational Model (MM), Combined TAM and TPB (C-TAM-TPB), Model of PC Utilization (MPUC), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). Venkatesh et al. (2003) concluded that behavioral intention is a strong predictor of actual use behavior and found four key determinants of behavioral intention and use behavior: *performance expectancy, effort expectancy, social influence*, and *facilitating conditions*. The first three of these determinants are direct determinants of behavioral intention and the last one is a direct determinant of use behavior. In Venkatesh et al. (2003) model, these four determinants are moderated by *gender, age, experience,* and *voluntariness of use.* The UTAUT model is depicted below in Figure 4.
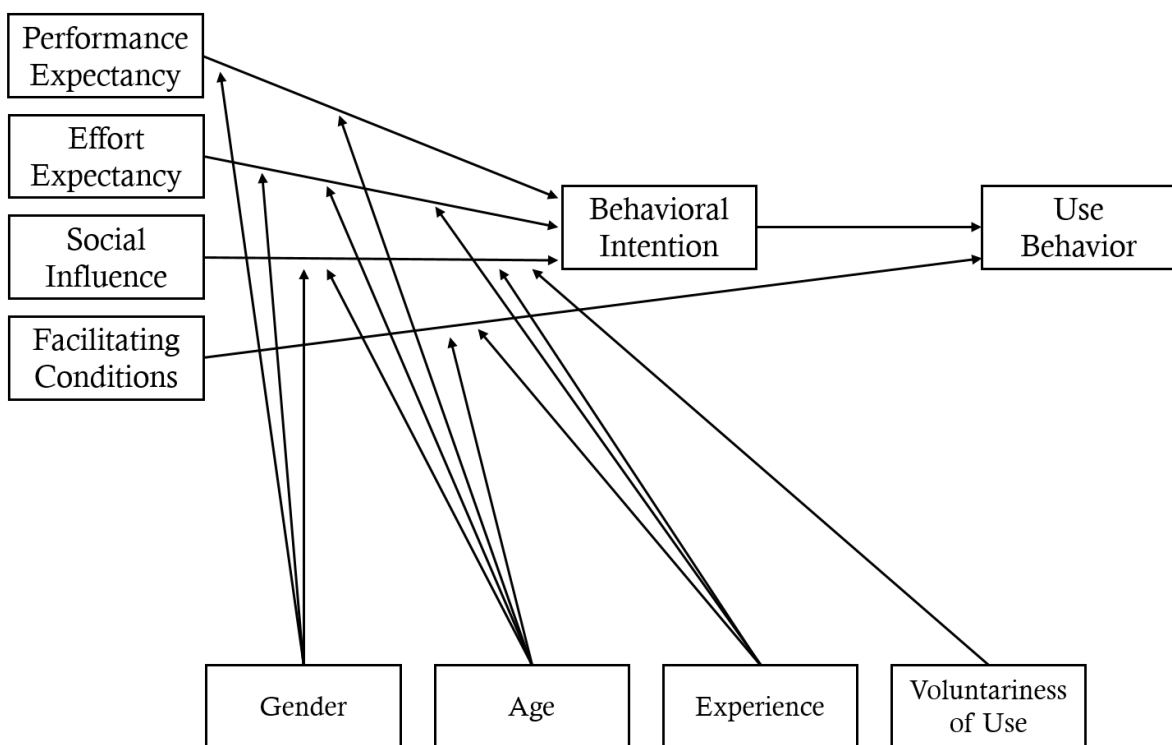
Figure 4. UTAUT model. (Venkatesh et al. 2003)

UTAUT2

UTAUT2 differs from its predecessor by adding three new key determinants to the model and leaving out the moderator of voluntariness. Also, in UTAUT2 the construct of facilitating conditions is seen to influence both, behavioral intention and the actual use behavior. The theory focuses on explaining IS adoption of consumers and the reason behind leaving out voluntariness from the moderators is that in a consumer context users have no organizational mandate to use a certain technology and most consumer behaviors are entirely voluntary (Venkatesh, 2012). The three new determinants in the UTAUT2 model are *hedonic motivation, price value,* and *habit*. These determinants as well as the

four remaining determinants from the UTAUT model are defined and discussed closer in the next section, 2.3. Research Model and Hypothesis Development. The UTAUT2 model is depicted below in Figure 5. The extensions presented in UTAUT2 improved the model significantly and according to Venkatesh et al. (2012) study, the variance explained in intention rose from 56 percent to 74 percent in the new model and the variance explained in technology use rose from 40 percent to 52 percent.
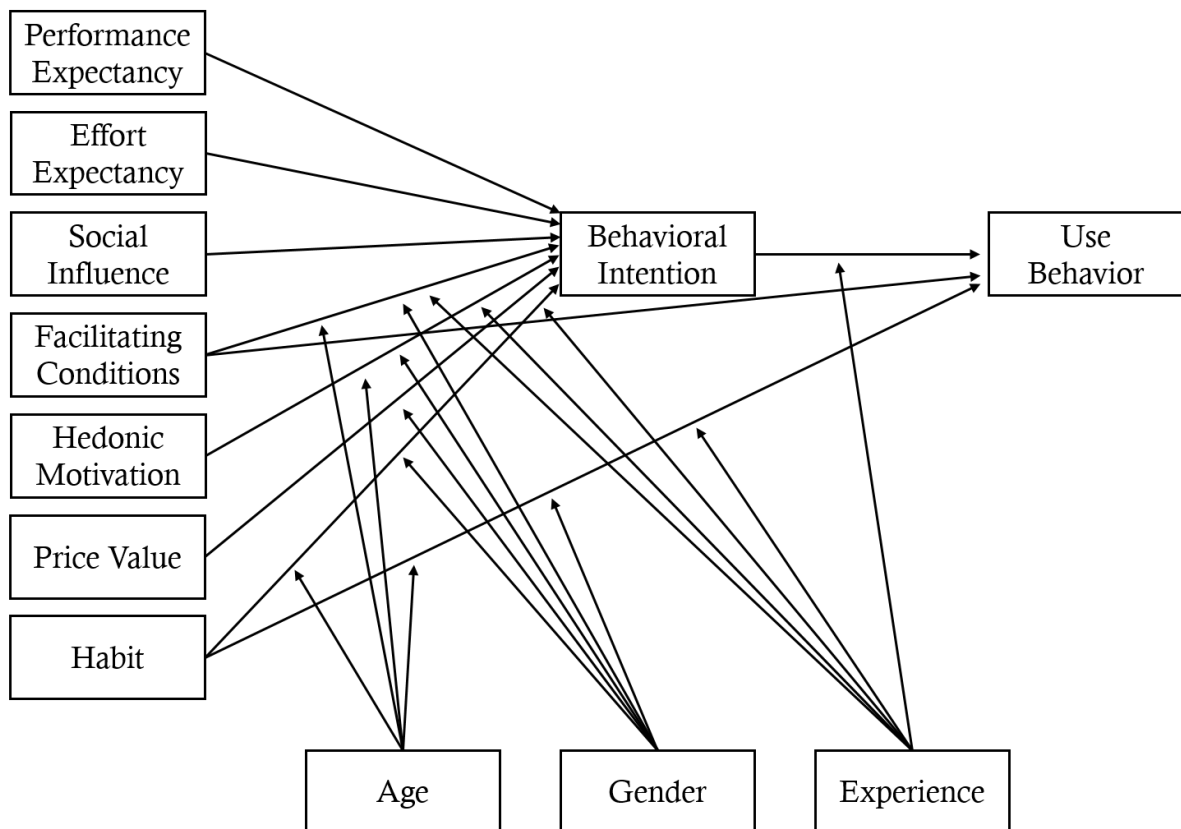
Figure 5. UTAUT2 model. (Venkatesh et al. 2012)

This study uses the UTAUT2 as a base for the research model and extends it to gain deeper insights about consumers' adoption of subscription-based music services. The UTAUT2 was chosen as the basis of the research model for mainly two reasons. Firstly, it is a unified combination of previous models used in IS adoption research. UTAUT2 is more extensive and performs statistically better than its predecessors. Secondly, unlike many other technology adoption models, UTAUT2 is designed to study consumer technologies. Two notable differences in the theory when compared to many others is that it assumes voluntariness and includes the factor of hedonic motivation. UTAUT2 model has been used to study the adoption of online music services (Martins 2013) and of other access-

based consumption technologies (e.g. Wong et al. 2014), but to the author's knowledge it has never been used to study the adoption of paid MaaS.

2.3 RESEARCH MODEL AND HYPOTHESIS DEVELOPMENT

The research model is constructed from the items used in previous IS adoption theories—mainly UTAUT2—and extended with the construct of tangibility preference, which is theorized to be a factor of behavioral intention as consumers are making a shift from a physical product to a digital one. This section explains each of the constructs in detail and presents the research model and the hypotheses of this study.

2.3.1 BEHAVIORAL INTENTION

Behavioral intention's (BI) effect on actual behavior stems from the basic concept underlying user acceptance research, which was presented earlier in this chapter (Figure 1). The link between BI and usage has been proved by multiple user acceptance studies and it is the key factor of usage in several theories, such as TPB, TAM, UTAUT and UTAUT2. Considering the strong link between BI and actual behavior in many of the previous user acceptance studies, we assume a corresponding link in the context of paid MaaS.

2.3.2 EFFORT EXPECTANCY

Effort Expectancy (EE) is "the degree of ease associated with consumers' use of technology" (Venkatesh 2012). EE is known as perceived ease of use in previous theories of user acceptance, such as TAM and TAM2. Some researchers have argued on the effects of EE and some claim that the significance of EE diminishes after users gain experience (Davis et al. 1989). As the majority of previous user acceptance of information systems research has concentrated on non-hedonic information systems, their results may not be directly applicable to the context of this study. In his study of adoption of hedonic information systems—which is a category into which paid MaaS falls into—Van der Hejden (2004) states that EE has a central role. EE has a strong link on user experience and the more effortless an information system is to use, the better its user experience is perceived. Previous music services research have results indicating for (Martins 2013) and against (Chu and Lu 2007, Koster 2007) the positive relationship between EE and behavioral intention. This research reasons that an easy to use music service would lower the users' non-monetary sacrifice of using the service and thus, EE would have a positive impact on the behavioral intention to use paid MaaS. Thus, I hypothesize that:

H1: Consumers' perceived effort expectancy is positively related to behavioral intention to use paid MaaS.

2.3.3 FACILITATING CONDITIONS

Facilitating Conditions (FC) are "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al. 2003). In a consumer context FC can be defined as the consumers' perceptions of the resources and support that they have available to perform a certain behavior (Venkatesh 2012). FC is equivalent to perceived behavioral control in TPB, where it refers to people's perception of the ease or difficulty of performing the behavior of interest (Ajzen 1991).

FC are seen to be a determinant of both behavioral intention and actual usage (Venkatesh 2012). According to the theory of planned behavior by Ajzen (1991), when a person has the intention to perform a behavior, facilitating conditions can be used directly to predict whether the behavior will be performed or not. For example, a person can have an intention to drive a boat, but if he feels that he does not have a favorable set of facilitating conditions, such as a boat that he could use or a person who would teach him how to navigate, the intention will never translate into behavior. In UTAUT2 however, FC is seen also as a direct determinant of intention. MaaS services are quite advanced technologies that require the support of other technologies such as computers with fast broadband internet or smart phones with 3G or preferably 4G network contracts, to ensure non-interruptive streaming. It can be thus assumed that facilitating conditions have a direct influence on the behavioral intention to use paid MaaS. I therefore hypothesize that:

H2: Consumers' facilitating conditions are positively related to behavioral intention to use paid MaaS.

2.3.4 HABIT

Habit (HT) is defined as "the extent to which people tend to perform behaviors automatically because of learning" (Limayem et al. 2007) and as "a repeated behavioral pattern that automatically occurs outside conscious awareness" (cited in Kim and Malhotra 2005). HT should not be confused with experience, which according to Venkatesh et al. (2013), is a necessary condition for the formation of habit but not sufficient on its own. They describe habit as a perceptual construct, which reflects a person's previous experiences.

HT was introduced to UTAUT2 after behavioral intention was no longer seen as the only predictor of technology use by studies that were conducted after the introduction of UTAUT (see Kim and Malhotra 2005, Kim and Narasimhan 2005, Limayem et al. 2007). These studies see HT as having a direct relationship with behavior as well as a moderating effect on behavioral intention. Kim and Malhotra (2005) argue that researchers have largely overestimated the intention-behavior relationship, because they have not taken past experiences and habit into consideration. According to Limayem et al. (2007) HT moderates the effect of behavioral intention to actual behavior and they claim that the more habitual a behavior gets, the less influence intention has on the actual behavior. Venkatesh et al. (2012) confirm the statements and prove the relationships between HT and intention as well as HT and behavior. A previous study in the context of online music services concluded HT as the strongest determinant of behavioral intention and a strong determinant of actual usage of online music services (Martins 2013). Hence, I apply the same reasoning to subscription-based music services and hypothesize the following:

H3: Consumers' habit is positively related to behavioral intention to use paid MaaS.

2.3.5 HEDONIC MOTIVATION

Hedonic motivation (HM) is "the fun or pleasure derived from using a technology" (Venkatesh et al. 2012). The term derives itself from the term *hedonism*, which is defined "the doctrine that pleasure or happiness is the sole or chief good in life" (Merriam-Webster 2016). Paid MaaS services are seen as hedonic information systems as their main purpose is to bring enjoyment to their users instead of being used to perform a utilitarian task. Van der Heijden (2004) explored user acceptance in hedonic information systems and found out that perceived enjoyment—an equivalent to HM—is a stronger determinant of behavioral intention than perceived usefulness in a hedonic system. His finding is supported by Venkatesh (2012) as well as previous user acceptance research of music technologies that state HM as being one of the most important determinants in adopting online music services (Martins 2013) as well as having a positive attitude towards piracy (Cesareo and Pastore 2014). It is also assumable that HM is a strong determinant of intention in the context of this research. I thus hypothesize that:

H4: Consumers' hedonic motivation is positively related to behavioral intention to use paid MaaS.

2.3.6 PERCEIVED USEFULNESS

In UTAUT2, perceived usefulness (PU) is labeled as performance expectancy. The two terms are synonymous and we use the term perceived usefulness, due to a measurement scale used in this research that was presented and validated by Chu and Lu (2007). Chu and Lu's measurement scale was chosen since it was built specifically for the context of digital music services. In UTAUT2, performance expectancy is described as "the degree to which using a technology will provide benefits to consumers in performing certain activities" (Venkatesh 2012) while Chu and Lu (2007) defined perceived usefulness as "the degree to which the consumer believes that listening to music online would fulfill the certain purpose." We will use the definition of Chu and Lu and add paid MaaS as the subject and refer perceived usefulness as the degree to which the consumer believes that listening to music via paid MaaS would fulfill a certain purpose.

Perceived usefulness has been confirmed as the strongest predictor of behavioral intention in several earlier information systems researches (Davis 1989, Venkatesh and Davis 2000, Jung et al. 2009). However, Van der Heijden (2004) argues that in hedonic information systems, perceived ease of use (effort expectancy) and perceived enjoyment (hedonic motivation) would be stronger determinants than PU. However, according to his findings, perceived usefulness also affects the behavioral intention in hedonic information systems. This positive connection has also been found in the context of online music services (Martins, 2013). Hence, I hypothesize that:

H5: Consumers' perceived usefulness is positively related to behavioral intention to use paid MaaS.

2.3.7 PRICE VALUE

Price value (PV) is conceptualized by Dodds et al. (1991) as the cognitive tradeoff between the perceived benefits received from using the application and the monetary cost for using it. In other words, PV is consumer's perceived value of a service minus the price of the service. Unlike in an organizational context where the costs of new technologies are usually handled by the organization and not the user, in a consumer context the user needs to finance the technologies by himself/herself. Thus, PV was an important addition to the UTAUT2 model.

PV is a critical factor in the adoption of paid MaaS as the services are competing with free alternatives like ad-based streaming and illegal file-sharing. It is argued that once a

consumer gets used to getting music for free via piracy, it will be difficult to convert them into paying customers (Kunze and Mai 2006). However, Dörr et al. (2013) found out that music pirates who had rejected legal music consumption before due to high prices may switch to MaaS services because the offer of MaaS services is new and valuable. PV has been found to have a direct impact on behavioral intention in previous research of consumer information systems, including online music services (Venkatesh 2012, Martins 2013). Hence I hypothesize that:

H6: Consumers' perceived price value is positively related to behavioral intention to use paid MaaS.

2.3.8 SOCIAL INFLUENCE

Social influence (SI) is "the extent to which consumers perceive that important others (e.g. family and friends) believe they should use a particular technology" (Venkatesh 2012). SI, also known as subjective norm in theories such as TRA, TPB, and TAM2, has found to be a strong predictor of behavioral intention either directly (Kwong and Park 2008) or through attitude (Chen and Chang 2013). SI has had a strong influence on behavior, especially in the case of adopting music services (Dörr et al. 2013). The reason behind the importance of SI in the context of music consumption is that the consumers have the possibility to acquire their music through illegal file-sharing, and the illegitimacy of this behavior can be condemned by their peers. On the flip side, the use of legal music consumption services such as paid MaaS can be encouraged by the important others of a consumer. The encouragement to use certain music services should not be underestimated as the social connectivity of these services can bring extra value to its users via the network effect. There are also controversial conversations in the media about the pros and cons of MaaS and for example artists' comments might have a notable effect on people's music consumption behaviors. I hypothesize that:

H7: Consumers' social influence is positively related to behavioral intention to use paid MaaS.

2.4 CONTEXT-BASED EXTENSIONS

The UTAUT2-based theoretical model is extended by one additional construct of tangibility preference to make the model more appropriate for the study of consumers' use and adoption of paid MaaS.

2.4.1 TANGIBILITY PREFERENCE

Tangibility preference (TP) was selected as an additional construct for the theoretical model. Tangibility refers to "the product's physical properties and the extent to which it can be seen, felt, heard, smelled, etc." (Freiden et al. 1998). As music consumption is in a transformation stage and music listeners are purchasing their music in physical (tangible) and non-physical (intangible) formats, TP is perceived to have a potential impact on consumers' choice of music consumption methods. TP is the consumer's preference of physical formats of music over the non-physical formats. Wagner and Hess (2013) found TP affecting behavioral intention to use paid MaaS indirectly through attitude, but the direct relationship between TP and BI has not been tested before. Styvén (2010) measured music listeners' tangibility preference and found out that music involvement and subjective music knowledge have a positive impact on TP and consumers who used MP3-players had generally a lower TP. Even though MaaS is in many ways a more convenient way of consuming music than CDs and vinyl, some consumers prefer tangible solutions. Consumers are often proud to display their physical record collections (Styvén 2010) and what increases the importance of record collections is that they are often expressive of one's identity (Belk 1988). However, Wikström (2012) argues that after the adoption of MaaS, the record collection as a reflector of identity is replaced by a steady flow of real-time information about musical experiences. Nonetheless, adopting paid MaaS requires a sacrifice, especially if the individual has a high TP when it comes to music. Therefore it would seem that an individual with a high TP would be less inclined to adopt paid MaaS. I thus hypothesize that:

H8: Tangibility preference is negatively related to behavioral intention to use paid MaaS.

2.5 RESEARCH MODEL

The research model used in this study is built from the nine constructs of EE, FC, HT, HM, PU, PV, SI, TP, and BI, identified and explained above. A visual representation of the research model is depicted in Figure 6 and the hypotheses are listed in Table 1.

Table 1. Hypotheses

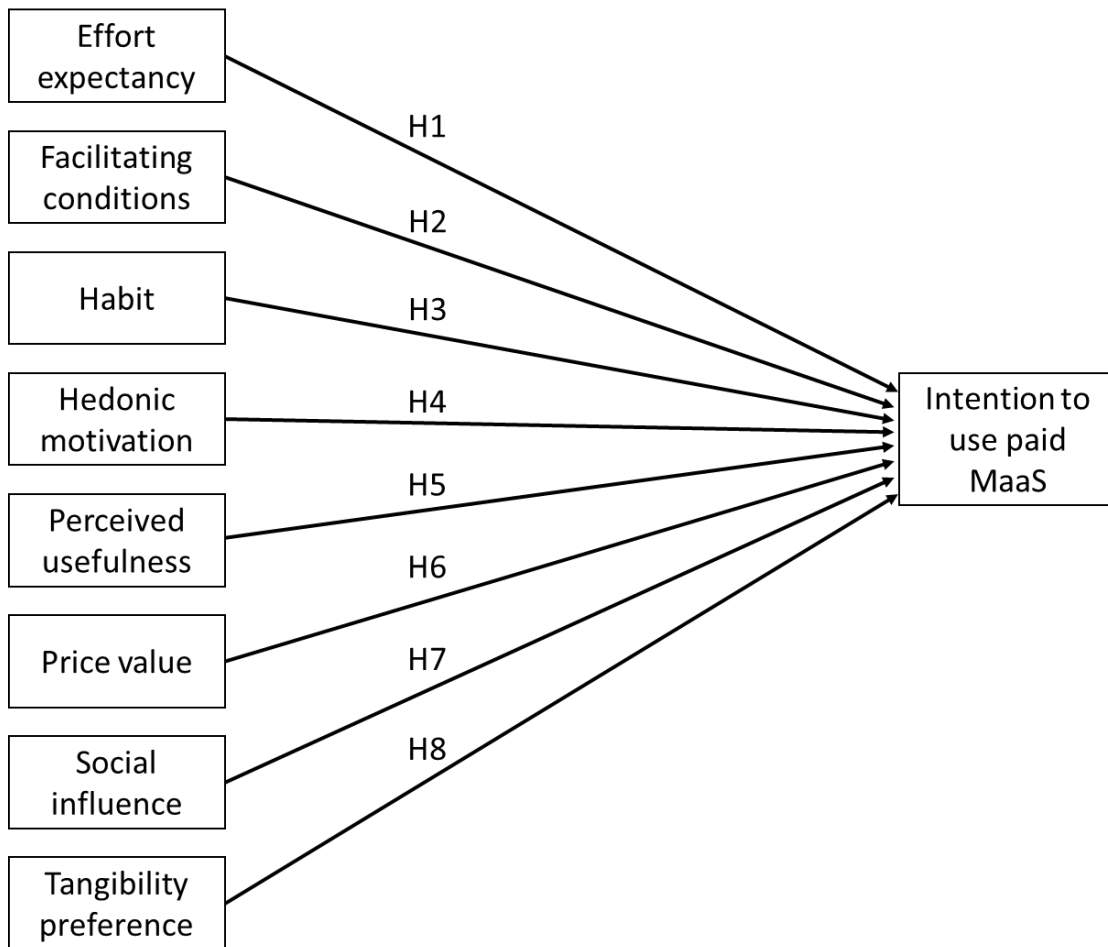| Hypotheses: |
| --- |
| *H1: Consumers' perceived effort expectancy is positively related to behavioral intention to use paid MaaS.* |
| *H2: Consumers' facilitating conditions are positively related to behavioral intention to use paid MaaS.* |
| *H3: Consumers' habit is positively related to behavioral intention to use paid MaaS.* |
| *H4: Consumers' hedonic motivation is positively related to behavioral intention to use paid MaaS.* |
| *H5: Consumers' perceived usefulness is positively related to behavioral intention to use paid MaaS.* |
| *H6: Consumers' perceived price value is positively related to behavioral intention to use paid MaaS.* |
| *H7: Consumers' social influence is positively related to behavioral intention to use paid MaaS.* |
| *H8: Consumers' tangibility preference is negatively related to behavioral intention to use paid MaaS.* |

Figure 6. Research model

3 METHODOLOGY

The data used to test the hypotheses was collected via consumer survey. This chapter describes the data collection, the sample characteristics, and the statistical analysis methods used to test the hypotheses.

3.1 DATA COLLECTION

The data was collected via online survey. The survey was built using Google Forms and it was distributed via Facebook and LinkedIn. The survey was up from February 26th of 2016 until March 14th of 2016. The sample collected is a convenient sample that consists of the researcher's social network. This might result in a certain type of bias as the researcher's social network consists largely by young, well-educated individuals. The survey link was seen by 560 people, from which 243 continued to browse the survey, and 136 of them answered the survey. This yields a response rate of 24.3%. The respondents could enter a raffle where one respondent was randomly selected to win a free month of Spotify Premium or a corresponding prize from a similar service. The perk was designed to get more participants to answer the survey and it might have increased the response rate. The sample size of 136 is quite small, yet sufficient to perform a structural equation model analysis. For example Gefen et al. (2000) and Ding et al. (1995) state that 100 to 150 is the required minimal sample size to conduct a structural equation modeling analysis. However, taken into consideration the complexity of the research model the achieved sample size is quite small and the statistical precision of the results may be doubtful. This is taken into consideration in the limitations of this research.

The respondents were able to take the survey in English or Finnish. In order to have a valid translation, the survey was first translated from English to Finnish and then the Finnish translation was translated back to English by a native speaker. That translation was then compared to the original survey to make sure that the questions do not differ. This is an approach suggested by Sekaran (2002) to ensure the validity of the translation. After the back translation, one question was noticed being significantly different from the original. The question was then revised in the Finnish translation and the same process was repeated with the modified question. After the question had been reformatted, there was no longer a difference between the original questionnaire and the back translation so the Finnish translation was confirmed to be valid. To ensure that the questionnaire was perceptible to

respondents it was pre-tested by five individuals. As no problems or misunderstandings arose, the survey was put online.

There were some missing data and two responses were deleted from the sample because the amount of missing data exceeded 10%, which is a threshold suggested by Kline et al. (1998) (cited in Byrne 2013). This left a total of 134 usable responses. In the final sample size of 134 there were only a few minor cases of randomly occurring missing data. A total of 9 missing values were imputed by using the median. Median was chosen to replace the missing values as they were of ordinal variable, measured using a seven point Likert scale. The data was also checked for unengaged answers by calculating the standard deviation of the answers of each respondent. The test did not produce any unengaged answers.

The survey was built by using validated measurement scales from existing academic literature regarding technology adoption and music services. The scale items were modified using minimal changes in wording to fit the context of paid MaaS and to test the presented research model. The survey items, measurement scales, and references are listed in Appendix A.

3.2 SAMPLE CHARACTERISTICS

This sections describes the characteristics of the sample in terms of demography and familiarity and usage of MaaS.

3.2.1 DEMOGRAPHIC CHARACTERISTICS

The respondents were identified by demographic characteristics of gender, age, and country. The demographic characteristics of the respondents are presented in Table 2. The gender distribution was slightly male dominated (Male 60.4%, Female 38.8%, Other 0.7%) but both traditional genders were well represented. The survey gave an option for respondents to specify their gender as "other" in case they feel that they are neither of the male or female gender (e.g. transvestite or androgyne). The data yielded one such respondent. The largest age group was clearly 26 – 30 year olds (56.7%) and 19 – 30 year olds represented a total of 90.3% of the respondents. The poor representation of other age groups can be explained by the convenient sample that consisted of the researcher's social network. Another reason for the uneven age distribution stems from the fact that young adults are the largest user group of MaaS. Even though the survey was designed for both, people who use and people who do not use MaaS, it is assumable that individuals with previous experience from the services were more inclined to answer. What might have

fortified the effect even further was the prize of free month of Spotify Premium. The uneven age distribution is not a large problem however, since young adults are the target market for MaaS companies. The respondents were mainly from Finland (82.8%) and rest of the participants were distributed between 13 other countries. The largest nationality among the respondents after Finland was Brazil (5.2%). The researcher was hoping for a more even distribution so that the results could be generalized on a global scale. Nevertheless, Finland is an interesting country to observe in the adoption of paid MaaS, because it is among other Nordic countries a market with best penetration by MaaS companies.

Table 2. Demographic characteristics

Demographic characteristics	Number of respondents (n=134)	%	Cumulative %
Gender			
Male	81	60.4	60.4
Female	52	38.8	99.3
Other	1	0.7	100.0
Age			
0 - 18	0	0.0	0.0
19 - 25	45	33.6	33.6
26 - 30	76	56.7	90.3
31 - 35	10	7.5	97.8
> 35	3	2.2	100.0
Country			
Finland	111	82.8	82.8
Brazil	7	5.2	88.1
Germany	4	3.0	91.0
USA	2	1.5	92.5
Other	10	7.5	100.0

3.2.2 RESPONDENTS' FAMILIARITY AND USAGE OF MAAS

To successfully measure the use and acquisition of paid MaaS it is important that the respondents possess a necessary knowledge and understanding of what paid MaaS is. To ensure this, free MaaS and paid MaaS, and their differences were explained to the participants in the beginning of the survey. On top of that, the respondents were asked, which MaaS services they are familiar with, if they have previously used a paid MaaS

service, whether they currently use free or paid MaaS services, and which distinct services do they use. All of the respondents were familiar with at least one MaaS service, Spotify being the most familiar of all. In fact, everyone of the 134 respondents knew what Spotify was. 88.1% of the respondents had used a paid version of MaaS before taking the survey and 70.1% of them was a current user. Many of the service providers offer free trials of their premium (paid) versions to attract customers and it was interesting to note that 19.4% of the respondents had used a premium version without paying for it. Presumably these individuals had either participated in a free trial or used the services with someone else's account. As such a large part of the sample was currently using a paid service (70.1%), there were actually more people paying for MaaS than using the free versions (35.1%). Spotify was notably the most used service in both categories, free and paid. What was interesting is that some respondents were using multiple services simultaneously, which might be the result of exclusive album releases (albums not released in all of the platforms at the same time), free trial periods, and service comparison. Again, the respondents' familiarity and use of MaaS services is well above the global level and even of that in Finland. Thus it might be impossible to generalize the results on a global scale. However, the result will reflect the perceptions of the most profitable user group for the music industry. Respondents' familiarity and use of MaaS services are listed in Table 3.

Table 3. Familiarity and use of MaaS services

Component	Number of respondents (n=134)	%	Cumulative %
Familiarity of MaaS services			
Apple Music	82	61.2	n.a.
Deezer	36	26.9	n.a.
Google Play Music	52	38.8	n.a.
Rhapsody	15	11.2	n.a.
Spotify	134	100.0	n.a.
TIDAL	28	20.9	n.a.
None of the above	0	0.0	n.a.
I have previously used paid MaaS			
Yes	92	68.7	68.7
Yes, but I have not paid for it	26	19.4	88.1
No	16	11.9	100.0
I currently use paid MaaS			
Yes	94	70.1	70.1

No	40	29.9	100.0

I currently use free MaaS

Yes	47	35.1	35.1
No	87	64.9	100.0

Current use of paid MaaS by service

Apple Music	8	6.0	n.a.
Deezer	0	0.0	n.a.
Google Play Music	1	0.7	n.a.
Rhapsody	0	0.0	n.a.
Spotify	90	67.2	n.a.
TIDAL	3	2.2	n.a.
None of the above	40	29.9	n.a.

Current use of free MaaS by service

Apple Music	5	3.7	n.a.
Deezer	3	2.2	n.a.
Google Play Music	4	3.0	n.a.
Rhapsody	0	0.0	n.a.
Spotify	37	27.6	n.a.
TIDAL	1	0.7	n.a.
None of the above	87	64.9	n.a.

Each construct with their means and standard deviations are presented below in Table 4. Each construct was measured by several items. The items were measured with a 7-point Likert-scale in which 7 represents 'strongly agree' and 1 represents 'strongly disagree'. The mean of behavioral intention to use paid MaaS was high (5.58), indicating that most of the respondents show intention to use the services in the future. The result comes as a no surprise as 70.1% of the respondents currently use the systems. Other high scoring constructs were effort expectancy, facilitating conditions, hedonic motivation, perceived usefulness, and price value, from which effort expectancy and facilitating conditions scored extremely high (6.13 and 6.06 respectively). This indicates that the respondents are skilled with new technologies and that the use of MaaS systems is easy for them. Habit, social influence, and tangibility preference were low scoring constructs (3.75, 3.54, and 3.27 respectively). Tangibility preference is expected to be so as it is hypothesized to be negatively correlated with behavioral intention to use paid MaaS, but the low values of habit and social influence are interesting. They give the indication that using paid MaaS

systems could be more a conscious choice to the consumers, than an action driven by habits or by the influence of others.

Table 4. Means and standard deviations

Construct	Mean	Std. Dev
Behavioral Intention	5.58	2.08
Effort Expectancy	6.13	1.07
Facilitating Conditions	6.06	1.18
Hedonic Motivation	5.54	1.36
Habit	3.75	2.33
Perceived Usefulness	5.54	1.56
Price Value	5.41	1.43
Social Influence	3.53	1.68
Tangibility Preference	3.27	2.05

3.3 STATISTICAL ANALYSIS METHODS

The data was analyzed using IBM's SPSS Statistics 23 and AMOS 23 software. The analysis method used for the research was a two-step, covariance-based structural equation modeling (SEM). SEM is an extension of several multivariate techniques of statistical analysis, most notably factor analysis and multiple regression analysis (Hair et al. 2010). It is a statistical method that takes a confirmatory approach to the analysis of a structural theory (Byrne et al. 2013). SEM is widely used and it is applicable when studying complex consumer behavior patterns with multiple variables and a series of interrelationships between the variables (Hair et al. 2010). The first step of SEM is to test the validity of the measurement model by a confirmatory factor analysis (CFA) and the second is the evaluation of the hypothesized paths with a structural model by seeing how the constructs are associated with each other.

3.3.1 CONFIRMATORY FACTOR ANALYSIS

Confirmatory factor analysis (CFA) was used to provide a confirmatory test of the measurement model—to verify the quality of the suggested latent constructs and to establish a statistically valid measurement model. CFA is used when a researcher has previous knowledge of the underlying latent variable structure. In this research, the knowledge is based on previous theory and the relations between the observed variables and the underlying factors are hypothesized a priori. The statistical structure of these

relationships are tested by CFA to determine the adequacy of goodness-of-fit to the sample data before moving on to test the hypotheses with the structural model. The CFA was done by using the SPSS Statistics 23 and the SPSS AMOS 23 software.

3.3.2 STRUCTURAL EQUATION MODELING

Second phase of the two-step SEM analysis was to structurally test the confirmed research model. The SEM analysis was done by using the SPSS AMOS 23 software. The structural model defines the causal relationships among the endogenous and exogenous latent variables (Gefen et al. 2000). More precisely, the structural model evaluates the hypotheses presented in the research model by assessing the relationships between the exogenous and endogenous constructs as well as their significance.

4 DATA ANALYSIS AND RESULTS

This chapter presents the executed data analysis process. First, the measurement model and its modifications are discussed and then the structural model, together with results of the hypothesis testing are presented.

4.1 MEASUREMENT MODEL

The first step of SEM analysis is to check the validity, reliability, and model fit of the measurement model. This process is known as the confirmatory factor analysis or CFA. In other words, CFA tests how well the measurement model fits with the empirical data collected, which in this case is the data retrieved from the online survey.

There are different types of validity that interest a researcher when conducting a SEM analysis, mainly content validity and construct validity. Content validity is also known as face validity, and it refers to the degree of correspondence between the selected items that constitute a summated scale and its conceptual definition (Hair et al. 2010). As the items and constructs used in this study are taken from previous literature with validated and proven scales, we can quite confidently assume content validity of our latent variables. Construct validity on the other hand is the extent to which a set of items that are designed to measure a certain theoretical latent construct actually reflect that construct (Hair et al. 2010). Having evidence of construct validity provides confidence that the items taken from a sample actually reflect the true score that exists in the population. There are many aspects of construct validity from which convergence validity and discriminant validity are often reported in IS research (Mäntymäki 2011). Convergent validity demonstrates that the indicator items of a specific construct converge or share a large proportion of variance in common (Hair et al. 2010). Convergent validity is measured by factor loadings and their significance, and average variance extracted (AVE).

When analyzing the initial measurement model, several items were noticed to have poor factor loadings. Hair et al. (2010) suggest that standardized factor loadings should be at least 0.5 and preferably 0.7 or higher, and Kline (2005) holds the value of 0.6 as the cutoff point for an item. The items with poor loadings were deleted to improve the model. These items were FC3, FC4, PU1, PU2, and TP3. Another issue with the initial model was that the constructs of perceived usefulness (PU) and hedonic motivation (HM) were correlating on a high level (0.889). The strong correlation between the constructs gave a poor discriminant validity for the model. PU also had a composite reliability (CR) of less than

0.7 (0.691) and as it did not function in the model by itself, the construct was deleted despite being presented in the research model. The reason for the high correlation between the HM and PU lies most likely in the fact that paid MaaS is a highly hedonic information system. If hedonic pleasure is a factor that consumers are looking for in an information system, they may interpret a system that provides more hedonic pleasure as being more useful. In other words, consumers perceive the pleasure derived from paid MaaS as usefulness itself. The deletion of PU construct rejects H5 of the original research model and the research model and hypotheses were revised. The new research model and hypotheses are presented below in Figure 7 and Table 5.
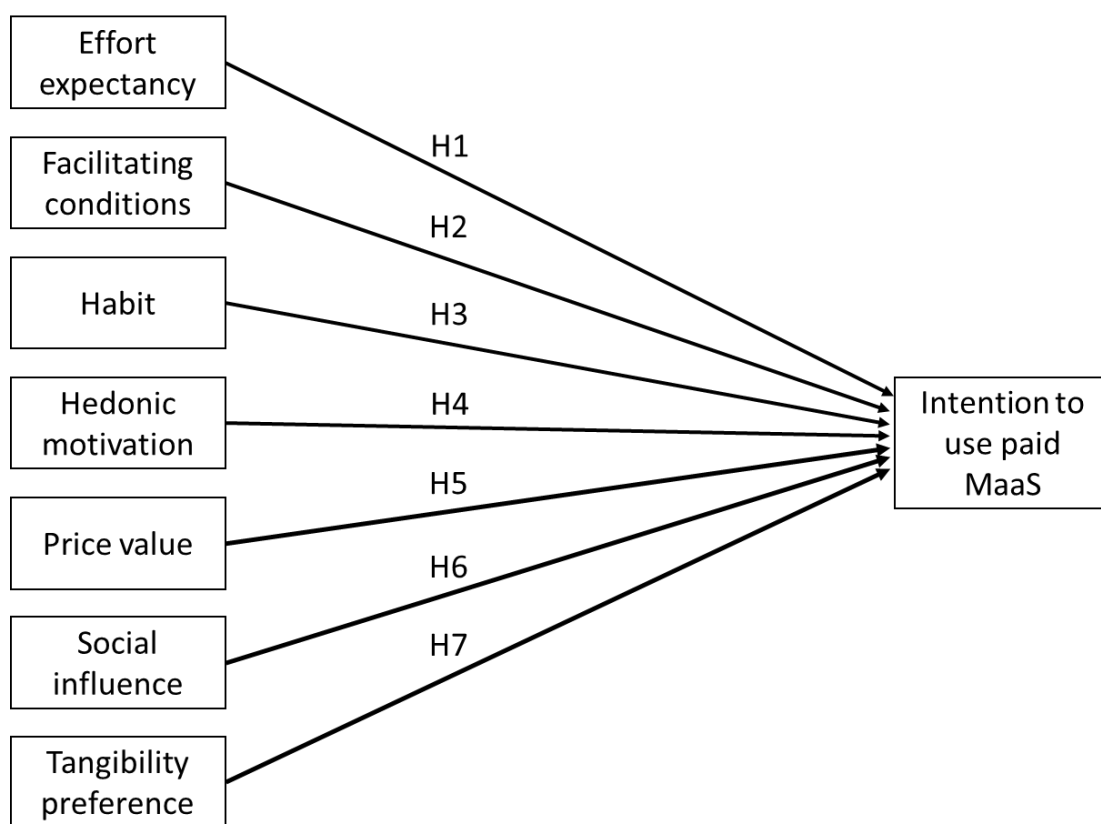
Figure 7. Revised research model

Table 5. Revised hypotheses

Hypotheses:
H1: Consumers' perceived effort expectancy is positively related to behavioral intention to use paid MaaS.
H2: Consumers' facilitating conditions are positively related to behavioral intention to use paid MaaS.
H3: Consumers' habit is positively related to behavioral intention to use paid MaaS.
H4: Consumers' hedonic motivation is positively related to behavioral intention to use paid MaaS.
H5: Consumers' perceived price value is positively related to behavioral intention to use paid MaaS.
H6: Consumers' social influence is positively related to behavioral intention to use paid MaaS.
H7: Consumers' tangibility preference is negatively related to behavioral intention to use paid MaaS.

Assessing overall model fit is an important part of the CFA and without a sufficient model fit, a researcher should not move forward with the analysis. After deleting the poor loading items and the construct of PU, the model fit indices were as follows: X^2: 384.492, df: 204, CMIN/DF: 1.885, CFI: 0.933, RMSEA: 0.082, PCLOSE: 0.000. The indices suggested a moderate model fit (except for the PCLOSE value that should be above 0.05). However, standardizer residuals were indicating otherwise. The item HT1 showed high standardized residual covariances, which according to Hair et al. (2010) should not be consistently over 2.5. If consistent values of above 2.5 are observed on the same item, it suggests that the item does not fit the model. HT1 had multiple standardized residual values that were too high and to ensure a good fit for the measurement model, the item was deleted from the model. Getting rid of the item improved the model fit indices substantially, presenting a great fit for the measurement model (X^2: 217.574, df: 183, CMIN/DF: 1.189, CFI: 0.986, RMSEA: 0.038, PCLOSE: 0.858).

To confirm the reliability and validity of the measurement mode, the average variance extracted (AVE), maximum shared variance (MSV), average shared variance (ASV), and composite reliability (CR) values were calculated. The values are presented in Table 6. along with the factor correlation matrix and the square root of AVE.

Table 6. Correlation matrix

	CR	AVE	MSV	ASV	HM	BI	EE	FC	HT	PV	SI	TP
HM	0.876	0.705	0.413	0.207	**0.840**							
BI	0.973	0.922	0.417	0.185	0.595	**0.960**						
EE	0.878	0.643	0.411	0.115	0.431	0.193	**0.802**					
FC	0.799	0.669	0.411	0.099	0.302	0.224	0.641	**0.818**				
HT	0.922	0.856	0.321	0.149	0.521	0.567	0.166	0.186	**0.925**			
PV	0.939	0.837	0.417	0.210	0.643	0.646	0.366	0.313	0.512	**0.915**		
SI	0.960	0.889	0.138	0.071	0.352	0.337	0.028	0.020	0.331	0.371	**0.943**	
TP	0.750	0.600	0.015	0.008	-0.112	-0.031	0.075	0.072	0.121	-0.071	0.118	**0.775**

Square root of AVE in bold.

The values on Table 6 prove a good validity and reliability for the measurement model. The AVE values are all well over 0.5, which suggests appropriate convergence. CR value indicates reliability and it should be above 0.7. The MSV and ASV values and the square root of AVE demonstrate discriminant validity (MSV and ASV should be less than AVE, and the square root of AVE greater than inter-construct correlations) (Hair et al. 2010). The scales of the final measurement model and the factor loadings are presented below in Table 7.

Table 7. Items and factor loadings

Construct	Loading	Item	Based on
Behavioral Intention (BI)	0.950	I intend to use premium music streaming services in the next three months.	Dörr et al. 2013
	0.959	I predict that I will use premium music streaming services in the next three months.	Venkatesh et al. 2003
	0.972	I plan to use premium music streaming services in the next three months.	
Effort Expectancy (EE)	0.861	Learning how to use a premium music streaming service is easy for me.	Venkatesh et al. 2012
	0.739	My interaction with a premium music streaming service is clear and understandable.	
	0.828	I find premium music streaming services easy to use.	
	0.774	It is easy for me to become skillful at using premium music streaming services.	
Facilitating conditions (FC)	0.716	I have the resources necessary to use premium streaming services.	Venkatesh et al. 2012
	0.909	I have the knowledge necessary to use premium streaming services.	
Hedonic Motivation (HM)	0.832	Using a premium music streaming service is fun.	Venkatesh et al. 2012
	0.934	Using a premium music streaming service is enjoyable.	
	0.716	Using a premium music streaming service is very entertaining.	
Habit (HT)	0.864	I am addicted to using premium music streaming services.	Venkatesh et al. 2012
	0.982	I must use premium music streaming services.	
Price Value (PV)	0.806	Premium music streaming services are reasonably priced.	Venkatesh et al. 2012
	0.954	Premium music streaming services are a good value for money.	
	0.975	At the current price, premium music streaming services provide a good value.	
Social Influence (SI)	0.960	People who are important to me think that I should use premium music streaming services.	Venkatesh et al. 2012
	0.947	People who influence my behavior think that I should use premium music streaming services.	
	0.920	People whose opinions that I value prefer that I use premium music streaming services.	
Tangibility Preference (TP)	0.801	For me it is important to have music in physical format.	Styvén 2010
	0.750	I feel that LP (vinyl) format is more "real" and genuine.	

*All loadings are significant at $p < 0.001$

4.2 STRUCTURAL MODEL

After confirming the measurement model in CFA, a researcher can move on to evaluate the hypotheses via SEM. Analyzing the structural model entails first, establishing model fit and second, testing the hypothesized paths.

The model fit indices remain unchanged after transforming the measurement model into a structural model (X^2: 217.574, df: 183, CMIN/DF: 1.189, CFI: 0.986, RMSEA: 0.038, PCLOSE: 0.858). The indices portray a great model fit.

Next, the hypothesized paths are evaluated. Hypotheses H3, H4, and H5 were supported and hypotheses H1, H2, H6, and H7 were rejected due to non-significant p-values. The path coefficients and p-values are presented in Figure 8 and Table 8. The path coefficients of the supported hypotheses are considered typical in size (Kline 2005). The R^2 value of 0.53 implies that the model explains 53% of the variance of consumers' behavioral intention to use paid MaaS.
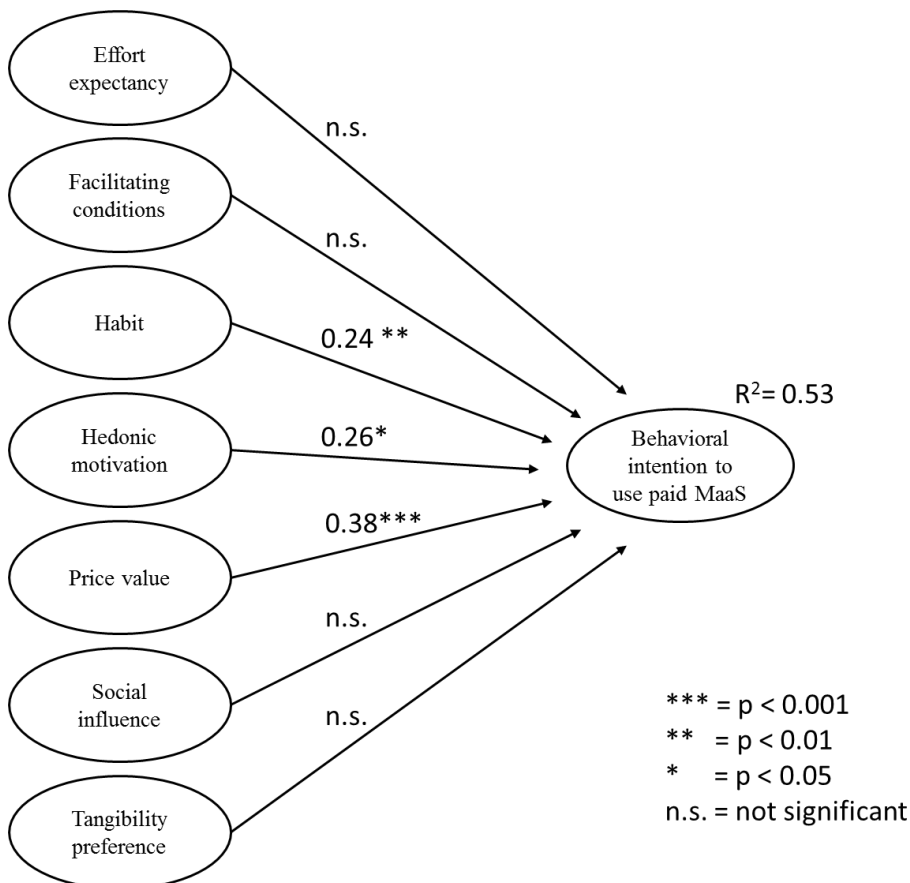

Figure 8. Structural model

Effort expectancy (EE) and facilitating conditions (FC) were hypothesized to have a positive influence towards the behavioral intention to use paid MaaS. As illustrated in

Figure 8, the effect of EE and FC were both insignificant (β_1 = -0.144, p = 0.164 and β_2 = 0.077, p = 0.425) and thus, H1 and H2 were not supported. This means that the easiness to use a paid MaaS system and the conditions that favor consumers' ability to use the system are not determining factors in relation to behavioral intentions to use paid MaaS.

Habit (HT) was found to be a determinant of behavioral intention to use paid MaaS (β_3 = 0.241, p = 0.004), supporting H3. The finding indicates that consumers form a habit of using paid MaaS and that HT predicts consumers' behavioral intentions to use paid MaaS. The result supports previous literature where HT was found to be a strong predictor of actual usage to use online music services (Martin 2013).

Hedonic motivation (HM) was hypothesized to influence people's intentions to use paid MaaS. The hypothesis is supported (β_4 = 0.255, p = 0.015), which means that the pleasure derived from using paid MaaS influences consumers' willingness to use the systems. H4 is thus supported, which is in line with previous music services adoption literature (Chu and Lu 2007, Martins 2012). The finding also supports Van der Hejden's (2004) claim that in a hedonic IS system HM will become a stronger predictor of behavioral intention than PU and EE.

The SEM implies that price value (PV) is the strongest determinant of behavioral intention to use paid MaaS (β_5 = 0.375, p < 0.001). H5 is thus supported. PV had also been found to be the strongest determinant of paid MaaS usage by Wagner and Hess (2013). The result suggests that the more the benefits gained from using a paid MaaS outweigh the monetary sacrifice, the more inclined a consumer is to use paid MaaS.

Social influence (SI) did not have predictive power on behavioral intention to use paid MaaS (β_6 = 0.031, p = 0.670) and thus H6 is rejected. The finding was contradictory to multiple earlier studies of music service adoption (e.g. Wang et al. 2009, Dörr et al. 2013, Wagner and Hess 2013). The finding implies that consumer's important others and their opinions do not have a significant effect on whether a consumer will consume music via paid MaaS.

H7 was added to the research model to extend the UTAUT2 theory to better fit the context of paid MaaS and it suggested that tangibility preference (TP) would have a negative effect on behavioral intention to use paid MaaS. However, the hypothesis was rejected (β_7 = -0.003, p = 0.970). People's preferences of physical products does not act as a direct determinant of behavioral intention to use paid MaaS.

In addition to these hypotheses, the hypothesized influence of perceived usefulness (PU) to behavioral intention to use paid MaaS was rejected earlier to improve the structural model. Hence, we can determine that PU is not an influential factor to consumers' intention to use paid MaaS. In conclusion, H3, H4, and H5 were supported. The factors of HM, HT, and PV explain 53% of the variance of consumers' behavioral intentions to use paid MaaS.

Table 8. Summary of research hypotheses

Path	Standardized estimates	p-value	Hypothesis
EE → BI	-0.144	0.164	H1: Not supported
FC → BI	0.077	0.425	H2: Not supported
HT → BI	0.241	0.004	H3: Supported
HM → BI	0.255	0.015	H4: Supported
PV → BI	0.375	< 0.001	H5: Supported
SI → BI	0.031	0.670	H6: Not supported
TP → BI	-0.003	0.970	H7: Not supported

5 DISCUSSION AND CONCLUSIONS

This concluding chapter discusses the results of this study. It then concludes the theoretical and managerial implications of the study, and lastly, discusses the limitations and gives suggestions for further research.

5.1 DISCUSSION

PV was the strongest determinant of behavioral intention to adopt paid MaaS. The finding suggests that MaaS companies should look for more ways to create value for their users and communicate the value of their service to the consumers in order to get more customers and to convert the users of freemium services into paying customers. It also reflects how music consumers have become very price sensitive as they can today access music for free through several different channels such as free streaming, radio, and illegal file-sharing services. Because consumers have gotten used to getting their music for free, music itself has lost its value and paid MaaS services should concentrate their efforts on building contextual value around music. It is also the only way that the companies can differentiate themselves from each other while they all offer comprehensive music libraries with more than 30 million songs (Kasternakes and Bi 2015). Because paid MaaS are competing with free alternatives and because most of the paid MaaS companies also provide freemium services themselves, it is vital that the consumers understand the benefits that they achieve when switching to paid MaaS. These benefits need to be communicated especially for those consumers who keep using the free MaaS model while the more advanced paid MaaS is available, because free MaaS is cannibalizing the sales of paid MaaS. Potential ways to increase value for MaaS users are for example, better search functions, curation, recommendations, social sharing, organizing favorite music experiences in convenient ways, and selling concert tickets and fan merchandise via the service. MaaS providers should also evaluate whether additional models between the free and premium services could serve customer groups that are not satisfied with the benefits of the free version nor the price of the premium version.

HM was the second strongest determinant of behavioral intention in our model. This is new information as HM's relation to BI has not been previously studied in the context of paid MaaS. The finding implies that paid MaaS is an extremely hedonic IS system as HM acts as a powerful indicator of BI to use paid MaaS and the traditionally dominant predictors of IS system usage of PU and EE were found insignificant. Van der Hejden

(2004) had demonstrated the phenomenon earlier with other hedonic systems, but not to an extent where PU and EE lose their predicting effect on BI. HM and PU also correlated highly with each other, suggesting that as an information system becomes more hedonic, the difference between playfulness and usefulness dissolves. The influence of HM to the behavioral intention to use paid MaaS suggests that the service providers should try to increase the pleasure derived from using their services. Music as a product is already one that delivers pleasure to its listener, but as the services are building more content around the music, they should focus on the hedonic value that the new content can generate. The content that the MaaS services create around the music can work as a key differentiator from other music consumption alternatives and from direct competitors. The potential ways in which paid MaaS providers could increase the hedonic pleasure of their users are very much the same as the ones that create value for their customers for example, the aforementioned search functions, curation, and recommendations. The companies should also consider providing other music related material that convey enjoyment and pleasure, such as music videos, interviews, concert recordings, and virtual reality experiences.

The third most influential construct to influence the behavioral intention to use paid MaaS was HT, which implies that consumers have a regular need to consume music. The finding has a lot of important implications for the MaaS providers. Firstly, it is important for the MaaS services to create a habit for their users so that they would tune in on a frequent basis and keep using the service. One clever way that a paid MaaS provider is already doing so is Spotify with their "discover weekly" playlists. The playlist provides a set of songs that change each week and that are built according to the user's listening preferences. After ten weeks, the tracks had been streamed for over 1 billion times (Spotify 2015). Other ways to harness consumers' habitual behavior is to create other captivating content, such as highlights of new album releases. Integrating paid MaaS into devices and spaces where people have a habit of listening to music, such as cars could increase the adoption of the services as well. The proved influence of HT also speaks for the current freemium model that is used by several paid MaaS companies. If the firms are able to create a habit for the freemium users, they may be more inclined to start using the paid service. The downside is that a user who creates a strong habit of using the free version might not upgrade to the premium version due to their habit of using the free version. Thus, free trials and partnerships with service providers and telecommunications operators may be more effective ways for the paid MaaS providers to acquire clients than the freemium. When a

consumer uses a paid MaaS service during their free trial, they may develop a habit of using the service and continue as a paying customer after the free trial expires.

The constructs of EE, FC, SI, TP, and PU were not found to influence the behavioral intention to use paid MaaS. EE and FC had both very high means among the respondents (6.13 and 6.06 on a scale from 1 to 7, respectively). This suggests that the respondents were very knowledgeable of using the technology and that they have favorable conditions to use it. Previous studies of online music service adoption have also failed to find a relationship between EE and BI (Chu and Lu 2007, Koster 2007). Moreover, the role of EE on BI has been often argued and many researchers have found EE affecting BI indirectly through PU and attitude (e.g. Kwong and Park 2008, Zhou 2008). Kunze and Mai (2007) claim that EE is actually more of a competitive necessity for an IS system, rather than a competitive difference-maker. Hence, the paid MaaS services should not ignore the easiness of use even though it does not seem to directly affect the behavioral intention to use the services.

FC's influence on BI was insignificant as it has been in previous studies of paid MaaS (Dörr et al. 2013, Wagner and Hess 2013). However, Koster (2007) found FC to have influence on BI that was moderated by the users' experience. Thus, it might be that the level of insignificance of the construct is due to a sample that is predominantly experienced in using paid MaaS services. Here it is also important to take note that the majority of the respondents were based in Finland, which is technology-wise a very developed country. While consumers do not seem to have difficulties in using paid MaaS in Finland where the internet and mobile connectivity is good, the situation might be totally different in a country such as India that has problems in internet connectivity and electricity distribution.

Unlike many previous studies suggest (e.g. Wang et al. 2009, Dörr et al. 2013, Wagner and Hess 2013), SI was not found to be a significant determinant of BI. The contradictory finding implies that music consumers base their consumption methods on their own reasoning rather than to the opinions of others. SI has previously been one of the strongest determinants of BI in music services research, but the studies have usually concentrated in determining what makes consumers pirate music, not what makes them use legal channels such as MaaS. Because piracy is illegal, people tend to have stronger opinions about using non-licensed file sharing services, which would explain why SI is not an influential factor anymore in the context of paid MaaS. The markets are not as black and white between

legal and illegal alternatives as they used to be and the abundance of services may have had a weakening effect on the power of people's recommendations.

TP did not predict behavioral intention to use paid MaaS. The finding can be considered positive for the MaaS providers as it implies that even people who would prefer tangible products are willing to use digital services. However, as the sample was not representative of the entire population but rather the younger generation, it might be that with older generations who have more experience using tangible music products, TP might be a determinant factor.

The indication that PU is not a determinant factor in predicting paid MaaS usage is interesting as PU has been the most dominant factor in determining the adoption of many other IS services. However, in more hedonic systems, the influence of PU to BI has generally been lower. The finding suggests that with highly hedonic IS systems, such as MaaS, people are not looking to accomplish things as, but instead they use the systems to seek for pleasure, and pleasure only. The author claims that in a highly hedonic IS systems usefulness as a determinant factor of behavioral intention blends in with HM or it may even disappear entirely.

5.2 CONCLUSIONS

The aim of this study was to examine the factors that lead consumers to adopt paid MaaS services, so that the music industry could better govern the prevailing transition from physical to digital. This study uses well-known theories from the field of IS adoption to form a research framework and hypotheses, and does an extension to the previous IS adoption theories to examine whether tangibility is a factor of behavioral intention in an industry that is digitalizing and offering products in both, digital and physical formats.

The research question of this study was: *What factors lead consumers to adopt paid MaaS services?*

The study found out that price value, hedonic motivation, and habit are determinants of consumers' behavioral intention to use paid MaaS, and thus, factors that lead consumers to adopt paid MaaS services. Together the factors were able to explain 53% of the variance of behavioral intention to use paid MaaS. Other hypothesized determinants of behavioral intention to use paid MaaS were effort expectancy, facilitating conditions, perceived usefulness, social influence, and tangibility preference. These five determinants were not

found to have an influence on people's intentional usage of paid MaaS. The research has several managerial and theoretical implications, which are presented below.

5.2.1 MANAGERIAL IMPLICATIONS

This research focused more on finding managerial implications for the music industry than it did in developing new academic theories and thus there are multiple managerial implications, especially for the industry practitioners. With the help of this study, the music industry players can take actions to increase the amount of paid MaaS users and in that way, grow the entire industry. First of all, paid MaaS companies should look for ways to create more value for their customers while keeping the price of their services at its current level. More importantly, they should try to better communicate the value that their services create over the other existing music services. The study found out that paid MaaS users value pleasure over usefulness and the ease of use. The service developers should keep this in mind and try to include pleasure and enjoyment into the new features and services. Ease of use of the service should not be overlooked, even though it is not a significant determinant of usage as it may however be a necessary condition for music service adoption.

Music consumers tend to use music distribution services as a habit and many of them may not understand the advantages that paid MaaS provides to their listening experience. Paid MaaS services should try to take advantage of habitual behavior by creating service elements that make the users return to the service on a frequent basis. They should also keep giving out free trials so that consumers would become habitual users during the trial and continue their behavior after the trial expires. The freemium model used by multiple paid MaaS providers can work correspondingly but they include a risk that a user will become a habitual user of the free version. Thus, it is vital to communicate the benefits of the paid version over the free one. In order to attract new user groups, MaaS providers should evaluate whether they could provide additional models with varying features and price, in between the current free and premium models.

The managerial implications of this study go beyond the music industry and the results can be valuable in other innovative and highly hedonic industries as well, such as video and book industries. Especially the video industry has developed in a very similar manner as the music industry and streaming has had a similar disruptive effect on the video industry as it has on the recording industry. Other digitalized and hedonic consumer services should

concentrate on providing good price value and hedonic pleasure for their users, while exploiting consumers' tendency for habitual usage.

5.2.2 THEORETICAL IMPLICATIONS

The research brought new information to the new technology adoption literature by testing the UTAUT2 model in the context of paid MaaS music distribution systems, which is an innovative, disruptive, and highly hedonic context. The UTAUT2 model could explain more than half of the variance in behavioral intention, indicating that it is suitable for studying the adoption of paid MaaS. Hence this study proved the applicability of the UTAUT2 model to a new research context. However, only three of the factors were verified and most of the factors in the model did not show significant effect on people's behavioral intentions. This indicates that the model could be further improved to better suit for the study of IS adoption in a highly hedonic and innovative context.

There had only been a few previous studies that examined consumers' adoption of paid MaaS. Paid MaaS is a unique research context since the services are access-based and they function in an environment occupied by physical, free, and illegal consumption alternatives. The research sheds new light on the factors that are important for the adoption of hedonic, access-based IS systems, especially as the factors seem to differ from the ones governing behavioral intention in other contexts.

HM of consumers had not been earlier studied in the context of paid MaaS. HM was a strong indicator of behavioral intention, which is a new observation in this context. The finding supports Van der Hejden's (2004) claim that in a hedonic IS system the predictive power of PU and EE decreases and the importance of HM increases. In this research, PU and EE did not have predictive influence on behavioral intention, which suggests that the effect described by Van der Hejden might be even stronger the more hedonic an IS system is. Our findings also suggest that in a highly hedonic IS system the difference between HM and PU becomes vague and consumers experience pleasure as usefulness.

5.2.3 LIMITATIONS AND SUGGESTIONS FOR FURTHER RESEARCH

This research has some limitations that need to be considered. First of all, the sample of this study consisted mostly of young, technologically sophisticated individuals from Finland, which might show as biased results. Therefore the sample is not a good representation of the entire population and the results cannot be generalized to a global level. The respondents had also more experience in using paid MaaS services than the

general average, which might be a reason why factors such as EE and FC were found insignificant. In fact, the sample consisted mostly of people that are already using MaaS services to a certain extent. Thus, the results may indicate poorly how to get music consumers who are used to the physical product to switch into using paid MaaS, but rather how to get consumers that use other digital services such as free MaaS to start using paid MaaS services, and why the current users of paid MaaS are using the services. However, it can be claimed that the results adequately represent the perceptions of the main user group of paid MaaS services and the findings can be used to retain those customers. As the respondents and their markets are in the forefront of paid MaaS penetration, the result can be seen reflective of what the less developed markets will be like in the future. The sample size of this study was sufficient, yet small. Due to the small sample size there is a chance that the results do not reflect the true effect of a larger population.

The author's recommendations for future research is to investigate whether the behavioral intention to use paid MaaS differs with a different sample. Especially the constructs of FC and SI might be significant in different countries and cultures and the managerial implications can differ between global and local levels. As there are still large amounts of people who consume their music in physical format, it would be good to replicate this study with a sample that includes those consumers to see if the factors that affect their behavioral intention to use paid MaaS and the strengths of those factors differ from the results of this study. The research shed some light on the role of HM in a highly hedonic IS system. The author suggests researchers to investigate other highly hedonic IS systems and see whether HM and PU behave similarly in those systems. Because price value is the strongest determinant of intention to use paid MaaS it would be important to investigate what elements and features increase consumers' perceived value of a music streaming service. This way the service providers could focus their resources in improving the right kind of features to better serve the consumer-driven music markets. This research also revealed the importance of habit in music consumption, which brings about many interesting possibilities for further research. Firstly, since habit contributes to the behavioral intention to use paid MaaS, the companies would value the information of how they can develop habitual usage of their services. Secondly, paid MaaS providers have argued over the importance of the freemium model and it would be important to find out whether a habit of using the free MaaS is restricting users to adopt paid MaaS. These

results would be beneficial for many other industries as well that are using the freemium model to attract new customers.

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7 APPENDICES

Appendix A. Questionnaire items

Construct	Code	Items	Original items	Scale	Reference
Effort Expectancy (EE)	EE1	Learning how to use a premium music streaming service is easy for me.	Learning how to use mobile Internet is easy for me.	Seven-point likert scale	Venkatesh et al. 2012
	EE2	My interaction with a premium music streaming service is clear and understandable.	My interaction with mobile Internet is clear and understandable.		
	EE3	I find premium music streaming services easy to use.	I find mobile Internet easy to use.		
	EE4	It is easy for me to become skillful at using premium music streaming services.	It is easy for me to become skillful at using mobile Internet.		
Hedonic Motivation (HM)	HM1	Using a premium music streaming service is fun.	Using mobile Internet is fun.	Seven-point likert scale	Venkatesh et al. 2012
	HM2	Using a premium music streaming service is enjoyable.	Using mobile Internet is enjoyable.		
	HM3	Using a premium music streaming service is very entertaining.	Using mobile Internet is very entertaining.		
Perceived Usefulness (PU)	PU1	I can better decide which music I want to listen to than in the past.	I can better decide which music I want to listen to than in the past.	Seven-point likert scale	Chu and Lu 2007
	PU2	I can acquire music information more easily through premium music streaming services.	I can acquire music information more easily through the online music web sites.		
	PU3	Premium music streaming services provide a variety of music.	The online music websites provide a variety of music.		
	PU4	Overall, I find premium music streaming services useful.	Overall, I find online music web sites is useful.		
Price Value (PV)	PV1	Premium music streaming services are reasonably priced.	Mobile Internet is reasonably priced.	Seven-point likert scale	Venkatesh et al. 2012
	PV2	Premium music streaming services are a good value for money.	Mobile Internet is a good value for money.		
	PV3	At the current price, premium music streaming services provide a good value.	At the current price, mobile Internet provides a good value.		
Social Influence (SI)	SI1	People who are important to me think that I should use premium music streaming services.	People who are important to me think that I should use mobile Internet.	Seven-point likert scale	Venkatesh et al. 2012
	SI2	People who influence my behavior think that I should use premium music streaming services.	People who influence my behavior think that I should use mobile Internet.		
	SI3	People whose opinions that I value prefer that I use premium music streaming services.	People whose opinions that I value prefer that I use mobile Internet.		
Facilitating Conditions (FC)	FC1	I have the resources necessary to use premium music streaming services.	I have the resources necessary to use mobile Internet.	Seven-point likert scale	Venkatesh et al. 2012
	FC2	I have the knowledge necessary to use premium music streaming services.	I have the knowledge necessary to use mobile Internet.		
	FC3	Premium music streaming services are compatible with other technologies that I use.	Mobile Internet is compatible with other technologies I use.		
	FC4	I can get help from others when I have difficulties using premium music streaming services.	I can get help from others when I have difficulties using mobile Internet.		
Habit (HT)	HT1	The use of premium music streaming service has become a habit for me.	The use of mobile Internet has become a habit for me.	Seven-point likert scale	Venkatesh et al. 2012
	HT2	I am addicted to using premium music streaming services.	I am addicted to using mobile Internet.		
	HT3	I must use premium music streaming services.	I must use mobile Internet.		
Tangibility Preference (TP)	TP1	For me it is important to have music in physical format.	Important to have music in physical format.	Seven-point likert scale	Styvén 2010
	TP2	I feel that LP (vinyl) format is more "real" and genuine.	LP format more "real" and genuine.		
	TP3	I prefer to store music as digital files.	Prefer to store music as digital files.		
Behavioral Intention (BI)	BI1	I intend to use premium music streaming services in the next three months.	I intend to use MaaS in its premium (free) version in the next three months.	Seven-point likert scale	Dörr et al. 2013
	BI2	I predict that I will use premium music streaming services in the next three months.	I predict that I will use MaaS in its premium (free) version in the next three months.		Venkatesh et al. 2003
	BI3	I plan to use premium music streaming services in the next three months.	I plan to use MaaS in its premium (free) version in the next three months.		