ANALYZING SPOTIFY IN AZERBAIJAN USING A UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY 2

by

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Dedication

This thesis is dedicated to my grandmother, Dr. Aida Beybutova, who was the source of my motivation and inspiration throughout my studies.

I would also like to dedicate this work to my parents and friends, whose love and support have been integral to my life, particularly my doctoral journey.

Finally, I dedicate this work to my teachers, who shared their experience and knowledge with me. Without them, I could not have imagined this research.

Thanks to everyone who believed in me.

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ABSTRACT

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The emergence of music streaming services has been an essential breakthrough in music technology in the era of digitalization. Despite the large number of players in the global market, the Spotify platform has the leading position. By the end of 2023, Spotify had more than 602 million active users and operated in more than 180 markets.

Despite the global popularity and spread of music streaming services, limited literature examines the acceptance and use of this technology. Several studies suggest using UTAUT2 to analyze Spotify users' adoption (Walean and Rachmawati, 2018; Chandra et al., 2018; Amalina, 2019; Suhod et al., 2022).

Venkatesh et al. (2012) suggest testing UTAUT2 in different countries, age groups, and technologies, which helps to improve the applicability of this model in the context of technology adoption. Therefore, this study comprehensively analyzes the adoption of the music streaming service Spotify in Azerbaijan using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework.

Using a quantitative methodology, this study initially collected primary data from Spotify users living in Azerbaijan through a survey. The 5-point Likert scale responses were analyzed using the PLS-SEM techniques.

The study results showed that the proposed factors of the theoretical construct UTAUT2, performance expectancy (PE), effort expectancy (EE), price value (PV), and habit (H), had a significant positive impact; however, social influence (SI) had a negative effect on the behavioral intention (BI) of Spotify users in Azerbaijan.

Obtained results on the influence of several UTAUT2 determinants on the behavioral intention of Spotify users in Azerbaijan provide a comprehensive ground for developing further business strategies and optimizing the user experience of Spotify in the territory of Azerbaijan. Based on the findings of this investigation, Spotify can maintain its dominant position in the highly competitive music streaming market in Azerbaijan by attracting more new customers and retaining loyal customers more effectively.

Keywords

Music Streaming Services, Spotify, Technology Acceptance Theories, Technology Adoption, UTAUT2, Unified Theory of Acceptance and Use of Technology 2, Partial Least Squares, Confirmatory Factor Analysis, Structural Equation Modeling, PLS-SEM.

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LIST OF ABBREVIATIONS

MSS - Music Streaming Services

IFPI - International Federation of the Phonographic Industry

TRA - Theory of Reasoned Action

TPB - Theory of Planned Behavior

TAM - Technology Acceptance Model

SCT - Social Cognitive Theory

MM - Motivational Model

IDT - Innovation Diffusion Theory

MPCU - Model of PC Utilization

UTAUT - Unified Theory of Acceptance and Use of Technology

UTAUT2 - Unified Theory of Acceptance and Use of Technology 2

PE - Performance Expectancy

EE - Effort Expectancy

SI - Social Influence

FC - Facilitating Conditions

HM - Hedonic Motivation

PV - Price Value

H - Habit

BI - Behavioral Intention

UB - Use Behavior

AVE - Average Variance Extracted

CFA - Confirmatory Factor Analysis

SRMR - Standardized Root Mean Square Residual

SEM - Structural Equation Modeling

PLS - Partial Least Squares

HTMT - Heterotrait-Monotrait

VIF - Variance Inflation Factor

CHAPTER I:

INTRODUCTION

1.1 Introduction

Since the advent of ancient civilizations, music has played an essential role in the lives of communities and humanity. It united and created an emotional connection between people of different ages and cultural backgrounds. The significance of music in our cultural environment has led to the emergence of the music industry. Nowadays, the music industry is undergoing tremendous changes. Over the past century, the music industry has not only influenced the development of new genres and styles but has also contributed to creating new technologies through which listeners can enjoy music worldwide. With the advent of the Internet and the development of technology, the music industry has actively begun to digitalize. The emergence and growth of digitalization led to the illegal distribution of music on the Internet, which led to a sharp decrease in sales of physical copies.

In this regard, the concept of music streaming services appeared. They revolutionized how people consume and listen to music by providing access to a vast music library through an Internet connection. Music streaming services are functionally like other streaming services, offering audio content.

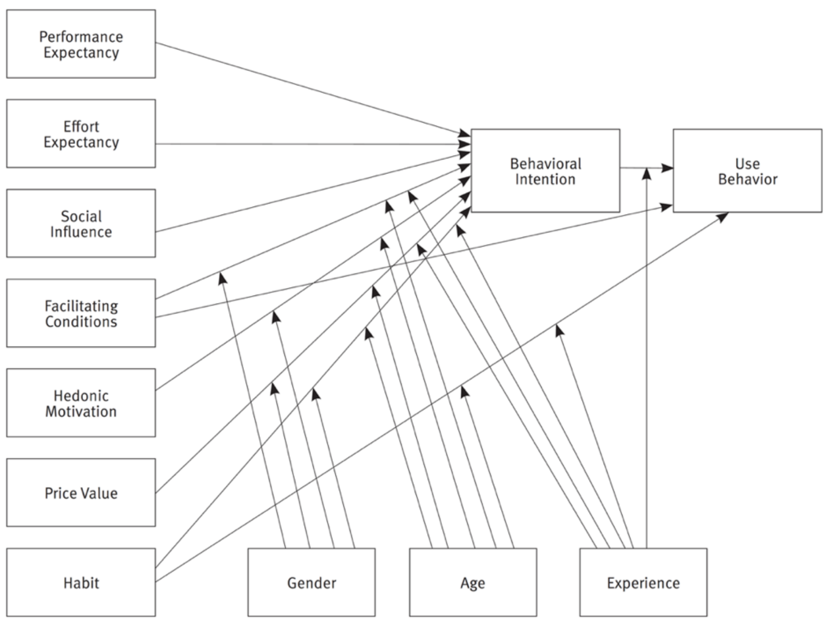
Usually, music streaming services have a similar business model. This is either a free version called freemium, which offers content in exchange for viewing advertisements, or a paid subscription taken every month. According to findings obtained from the International Federation of the Phonographic Industry (IFPI) official website, it is observed that in 2023, approximately 67.3% of the profits of this industry were garnered via streaming services (IFPI, 2024). The high profitability of MSS has led to an increase in the number of new players in the market that differ in design, functionality, and music content.

Spotify is a leader among music streaming services, and it was launched in Stockholm, Sweden, on 7 October 2008. It offers many songs and playlists, an attractive design, and an advanced recommendation system. Spotify is reported to have 602 million monthly active users, and 236 million are premium subscribers by the end of 2023. By the end of 2023, the Spotify platform operated in more than 180 markets.

The theoretical framework tested in this research is UTAUT2, developed by Venkatesh et al. in 2012. According to Venkatesh et al. (2003), integrating individual reactions, intentions to use, and actual use can demonstrate the theoretical approach to technology adoption. Unified Theory of Acceptance and Use of Technology 2 is a theoretical model developed to understand and predict user acceptance and adoption of technology. This theory relates to many other theories of technology acceptance. Park (2020) states that the UTAUT2 is designed based on the user's context and demonstrates statistically better results than other technology adoption models such as TAM and UTAUT. Barata and Coelho (2021) argue that music streaming platforms are information systems where the first models for adopting technology were implemented.

The Unified Theory of Technology Acceptance and Use 2 developed a framework consisting of the following determinants: performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), price value (PV) and habit (H) which in turn influence behavioral intention (BI) and use behavior (UB). Furthermore, the provided determinants are moderated by gender, age, and experience.

Figure 1. UTAUT2 Model



Source: Chen, L. Y., & Chen, Y. J. (2021). A study of the use behavior of line today in Taiwan based on the UTAUT2 model

1.2 Research Problem

Despite the global popularity and spread of music streaming services, limited literature examines the acceptance and use of this technology. According to Suhod et al. (2022), “despite the capability of this theory to predict behavioral intention (BI) of information system, the application of the UTAUT 2 model remained limited in the context of music streaming studies.” In addition, most studies in this area are aimed at a general analysis of music streaming services without a detailed analysis of specific platforms, creating a noticeable research gap. This also applies to conducting similar studies in different countries and regions in which a unique social and cultural character may be present. For instance, the chronological and distinctive development of folklore and the music industry differs significantly in Europe and Asia, which requires the study of specific contexts in different countries.

1.3 Research Purpose and Hypotheses

The purpose of this study is to comprehensively analyze the adoption of the music streaming service Spotify in Azerbaijan using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. This dissertation examines the influence of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit on the behavioral intention of Spotify users in Azerbaijan.

Therefore, the following hypotheses are formulated:

H1: Performance expectancy positively relates to behavioral intention to use Spotify in Azerbaijan.

H2: Effort expectancy positively relates to behavioral intention to use Spotify in Azerbaijan.

H3: Social influence positively relates to behavioral intention to use Spotify in Azerbaijan.

H4: Facilitating conditions positively relates to behavioral intention to use Spotify in Azerbaijan.

H5: Hedonic motivation positively relates to behavioral intention to use Spotify in Azerbaijan.

H6: Price value positively relates to behavioral intention to use Spotify in Azerbaijan.

H7: Habit positively relates to behavioral intention to use Spotify in Azerbaijan.

1.4 Significance of the Study

This research makes significant contributions to both academia and industry.

First, the research is innovative in terms of geographical context. This study is the first in Azerbaijan to fill the research gap in the previous analysis and literature review. Secondly, this study offers an in-depth analysis of the behavior of users of the most widespread music streaming service, Spotify, using the most current and comprehensive theory of technology adoption called UTAUT2. Rondan-Cataluña et al. (2015) argue that UTAUT 2 has higher predictive power than other technological adoption models.

In conclusion, from a practical side, the author's research outcomes and recommendations can help stakeholders, managers, and marketers of music streaming services improve their business techniques and strategies for attracting new clients, increasing customer loyalty satisfaction, and improving the user experience of music streaming platforms.

1.5 Structure of the Thesis

This study is organized into six chapters, each responsible for a specific understanding of the study. Taken together, these chapters provide a clear understanding and answer all the questions posed by the author.

Below are all the chapters with a brief description:

Chapter 1: Introduction

This chapter is of an introductory and significant conceptual nature in the study. The research problem, its purposes, and the importance of application in academic and business aspects are revealed. In addition, research hypotheses are presented, which will be discussed in detail in the following chapters of the dissertation.

Chapter 2: Literature Review

This chapter is divided into two parts. The first covers music streaming services, notably Spotify, from the point of view of features and role in modern business. At the same time, the second describes the chronological development of technology acceptance theories and, in particular, the theoretical framework of this study—UTAUT2, developed by Venkatesh et al. in 2012.

Chapter 3: Methodology

The determinants representing the UTAUT 2 model were taken from the study by

Venkatesh et al. (2012). This study presents the quantitative methodology underlying its theoretical design. First, it presents an exploratory research model that has also been used in studies by other authors investigating the adoption of music streaming services (Amalina, 2019; Barata and Barata, 2023). Next, the research design consists of sampling and data collection procedures will be shown. The following subsections describe the analysis of primary data obtained from a quantitative survey of Spotify users in Azerbaijan. The reliability and validation of the study are also presented. Additionally, the final subsections provide information on ethical considerations and limitations in research design.

Chapter 4: Results

This chapter shows and analyzes the primary data obtained through a quantitative survey. This study implements the SmartPLS 4 software for implementing structural equation modeling (PLS-SEM).

This chapter consists of three main parts. The first part describes the demographic characteristics of survey participants and provides information on descriptive statistics.

The next part is devoted to creating a measurement research model by assessing the reliability and validity of its constructs.

In the final part, a structural model of the study is created using the bootstrapping technique, and the path coefficients of the research constructs are measured.

Chapter 5: Discussion

The study's findings are discussed within the proposed theoretical framework of UTAUT2. This chapter is a logical continuation and interpretation of the empirical results obtained in the previous chapters. The study results are subject to comparative analysis with earlier authors of similar studies.

Chapter 6: Implications, Recommendations and Conclusion

The final chapter details the implications of this research for academia and industry. It also discusses several critical methodological and practical recommendations for future research and concludes by summarizing all of this study's chapters.

Chapter II:

LITERATURE REVIEW

2.1 Introduction

The literature review of this study provides a holistic approach to exploring the topic of Spotify users' adoption in Azerbaijan. Since Spotify is an integral part of the history of music streaming platforms, the study first demonstrates the development of streaming platforms. It comes with critical statistics that justify the subject of this study. Continuing the theme of the rise of music streaming services, the investigation offers a history of the creation and development of Spotify, a detailed analysis of its business model in various countries, and an analysis of the technical features that helped Spotify gain popularity and leading positions in the global music streaming services market.

In recent years, the digitalization process of various technological fields has been actively developing in Azerbaijan, especially in the context of music streaming services. According to Statista's research (2023), the number of active paying users of music streaming services has grown from 400 to 600 thousand users from 2019 to 2023, which provides empirical evidence of rationale for this research. Moreover, there is a significant increase in the income of music streaming services in Azerbaijan from 2.74 to 5.77 million USD from 2017 to 2023 (Appendix C). In addition, Spotify is the most widespread product among music streaming services in Azerbaijan. According to Statista (2022), Spotify's brand share in Azerbaijan was 52%, significantly higher than that of competitors such as Apple Music (22%), YouTube Music (15%), etc.

The literature review continues with an introduction to the study of technology acceptance theories. This sub-chapter describes the basic concepts and benefits of using technology acceptance theories in academia and industry. The literature review continues with a chronological overview of all the major theories and models of technology acceptance that have existed throughout time. It is worth noting that this sub-chapter plays a significant role in the comparative analysis of previous theories of technology acceptance with the theoretical construct used in this study. This chapter concludes with the consideration and development of research hypotheses. The study suggests that the seven factors of the original UTAUT2 framework positively influence the behavioral intentions of Spotify users in Azerbaijan. A critical analysis of the authors in the field of the adoption of music streaming services accompanies each hypothesis of this investigation.

2.2 Music Streaming Services

With the development of streaming services in the early 21st century, people worldwide gained access to various content types. Content includes films, music, podcasts etc. Spilker and Colbjørnsen (2020) mentioned that the first use of streaming dates back to approximately the 1970s; meanwhile, this term has been broadly used since the 1980s. The same authors argue that streaming had a local designation at that time. For instance, one computer could convey the data to another through a local network, or the user could watch while recording on the same computer.

Currently, many streaming services exist, including video (Netflix, Disney+), music (Spotify, Apple Music), gaming (Twitch), and files (Dropbox, Google Drive).
In recent years, music streaming services have become increasingly popular. Datta et al. (2018) state that streaming has revolutionized the music industry. First, these platforms allow listeners worldwide access to a vast library of audio content by enabling them to connect through smartphones, computers, and other electronic devices (Lozić and Vojković, 2020). Secondly, music streaming services allow people to create and share unique playlists with others (Hracs and Webster, 2021).

The popularity of music services is determined by the increasing number of new significant players in the global market and the annual increase in the total number of active users. According to the MIDiA study for 2022, approximately 80% of music listeners use music streaming services. Notably, the number of music streaming service subscribers has grown approximately tenfold since 2015, with more than 616 million users as of mid-2022.

Table 1. Music Streaming Subscribers over time

Year	**MSS Subscribers**	**Increase in %**
Q4 2015	68 million	-
Q4 2016	100.4 million	+47.6%
Q4 2017	198.6 million	+97.8%

Q1 2018	229.5 million	+15.5%
Q1 2019	304.9 million	+32.8%
Q4 2019	341 million	+11.8%
Q1 2020	400 million	+17.3%
Q4 2020	443 million	+10.7%
Q1 2021	487 million	+9.9%
Q2 2021	523.9 million	+7.6%
Q2 2022	616.2 million	+17.6%

Source: Adapted from MIDiA (2022).

The popularity of music streaming services can be attributed to the ability to listen to a large selection of licensed audio content and to their affordability compared to physical CDs, which had to be purchased at specialized music stores and required a dedicated playback device. Eggers (2018) argues that while physical discs would make more money, artists gain deep access to data about who listens to their songs, how many users, what albums and tracks, etc., through music streaming services.

Today, people of different ages and geographical locations actively use music streaming services, but the age distribution remains uneven. Chandra et al. (2018) claim that young people are more likely to use digital products because they are more likely to use their smartphones. Looking at the demographics of music streaming service users, according to IFPI Research (2022), the majority are younger generations who have quickly adapted to the digitalization of the music industry.

Table 2. Music Streaming Age Proportion

Age	Proportion Who Stream Music
16-24	54%
25-34	56%
35-44	44%
45-54	36%
55-64	26%

Source: Adapted from IFPI (2022).

The growing popularity of music streaming platforms among listeners significantly increases revenue dynamics yearly (Chen et al., 2018). The music streaming services are a highly considerable business field, holding immense potential for substantial commercial expansion and advancement. According to the IFPI (International Federation of the Phonographic Industry) (2024), Streaming is also the medium of recorded music that generates the most income, constituting 67.3% (48.9% for streaming subscriptions & 18.5% for ad-supported streams) of the global recorded music industry's revenues in 2023, a total of $28.6 billion. Streaming has generated more yearly income, with an 11.2% growth in 2023.

Many music streaming services today have a similar business model. Typically, this is either a free version with many functional limitations and display of advertisements, called “freemium,” or a paid version that charges the user a certain amount for a monthly or annual fee (Barata and Barata, 2023).

It's important to consider how artists who publish their content on music streaming services make money. The model by which an artist is paid is called “pay per stream,” which means a fee for each listener. In general, the more engagement a musician has in his account, that is, subscribers and the number of plays, the more income he receives from music streaming services (Chen et al., 2018).

In addition to the typical business model described above, music streaming services benefit from gathering users’ data. Webster (2023) states that music streaming services gather various data based on listeners' tastes, searches, and playlists. Furthermore, while the consumer creates an account, the music streaming services receive age, location, and other demographic data.

Personal data is a valuable resource for creating additional income streams. Businesses use this tool differently, but it essentially revolves around tailoring experiences that develop mutually beneficial relationships between companies and their consumers. This helps attract customers to the business faster as they receive personalized offers, and the industry, in turn, gains a more loyal customer base. For example, music streaming services rely on this collected data to determine precisely the audio content that the user wants. This implementation is frequently called personalization.

Webster (2023) argues that personalization is a technique for providing consumers with certain information, such as goods and services. The same author claims that personalization offers a method to find appropriate music depending on the mood and activities of listeners while assisting creators in finding the relevant audience. It is no secret to anyone that personalization is one of the critical success formulas in the competitive music streaming services market. Ogden et al. (2011) mentioned that it's complicated to predict appropriate channels in the future; however, it will likely suppose technology and greater personalization.

Despite the similar concept and business model, music streaming services still have some differences in functionality. Hracs and Webster (2021) noted that apart from cost, music streaming services attempt to differentiate themselves in content offerings, particularly with exclusive releases. Reichert (2019) writes that music platforms such as Apple Music, Spotify, Primephonic, and IDAGIO have some functions in common;" however, each separate player can be viewed as symbolizing something different." There are several categories into which music streaming platforms are divided. Interactive platforms include, for example, Spotify or Apple Music, which provide the freedom to choose any of the existing compositions for listening, while non-interactive ones, such as Pandora, provide playlists based on the listener's preferences when working with radio stations. Additionally, music streaming platforms vary in their focus on mass or niche products. Hesmondhalgh (2021) claims that small niche products such as IDAGIO for classical music or platforms allow free uploading of audio content like Soundcloud. Other than that, the same author argues that there is a difference between East and Western music streaming platforms. For example, Chinese streaming services are more integrated with social networks than Western competitors.

Despite the large number of global music services market players, several prominent players have held leading positions over the past few years.

Table 3. Music Streaming Market Share

Streaming Platform	**Proportion of Subscribers**
Spotify	30.5%
Apple Music	13.7%
Tencent Music	13.4%
Amazon	13.3%
YouTube Music	8.9%
Netease	6.1%
Yandex	2.2%
Deezer	1.5%
Others	10.2%

Source: Adapted from MIDiA (2022).

According to Table 3, Spotify is the leading brand among music streaming services, with more than a third of all subscribers in the global market.

2.2.1 Spotify: A Global Leader

The story of Spotify begins with the collaboration of two talented entrepreneurs from Sweden who had utterly different entrepreneurial experiences. According to Vonderau (2019), Spotify's founders, Daniel Ek and Martin Lorentzon, have no previous experience with music streaming services. Both of them have profound advertising experience. Daniel Ek founded several technological companies, such as Advertigo, an online advertisement platform, whereas Martin Lorentzon founded Tradedoubler in 1999. The same author states that in 2006, two successful entrepreneurs started a business together and named it Spotify. The name Spotify had no particular meaning.

Fleischer and Snickars (2017) argue that Spotify's concept was purely technological. Fleischer (2021) claims that Spotify initially started recruiting skilled networking developers who could create an exclusive technology for distributing data through the Internet using peer-to-peer technology, similar to file sharing. File sharing means sharing images, music, and video content.

Vonderau (2019) claims that the founders of Spotify, using their previous entrepreneurial experience, were able to recognize the necessary gap in the market successfully and, step by step, transformed their project into something marvelous. The idea was born out of Ek's frustration with music piracy and desire to create a legal alternative that would provide convenience and accessibility to users worldwide. Gierhart (2019) states that 165 million songs were illegally transferred daily before music streaming services appeared. Spotify’s founder, Daniel Ek, said in an interview: “From the very beginning, our vision was to offer a legal music service, as good or better than the pirate sites, giving users access to all music in the world, for free" (Eriksson et al., 2019).

In addition to the innovative idea of creating a streaming service for listening to legal music, Spotify also distinguished itself by developing a unique business model. Spotify became one of the popularizers of the now-famous freemium business model. Initially, it was decided to start with two different tariffs. The first so-called freemium, which included listening to music and podcasts with a relatively low quality of 160 kilobits per second and viewing many advertisements, brought additional profit to the company. The second tariff, the so-called premium, included listening to all songs without advertising 320 kilobits per second in high quality (Kreitz & Niemela, 2010). It is also worth considering that the free account does not allow users to download tracks for offline listening and enables users to listen to the content only in a "shuffle" mode (Amalina, 2019). It is important to note that the business model also had the feature of providing consumers with a trial version in which users received full functionality from the premium tariff free of charge for 1 to 3 months. After the trial period, the consumer could choose the main premium tariff but pay it monthly or switch to a free tariff with functional limitations. Furthermore, Spotify has developed a strategy to bring back customers who have stopped using the premium version by offering a trial period from time to time. In addition, various price discrimination strategies have been developed. For example, many countries today have exclusive student and family tariffs at a reduced price. An essential feature of Spotify's price discrimination policy is its geographical feature. This way, the countries and regions where Spotify is offered at different prices were designated. For example, an individual plan costs $4,99 in Azerbaijan, which aligns with rates in most Eastern European and some Asian countries. Denmark, on the other hand, boasts the highest price, at around $16 per month. In contrast, Nigeria offers the most economical monthly subscription, at almost $0.66. According to Durrani's (2024) research, despite price discrimination, Spotify's pricing policy is pretty competitive on average.

Table 4. Average Monthly Price for Music Streaming

Streaming Service	Monthly Cost
Spotify Premium	$10,99
Apple Music	$10,99
Tidal	$10,99
Amazon Music Unlimited	$9,99
YouTube Music	$10,99

Source: Adapted from Durrani (2024).

Considering Spotify's platform's profitability, it took several years to achieve positive financial results. Spotify took years and several rounds of investment to create, distribute, and grow. According to Fleischer and Snickars (2017), several funding series have totaled more than $1 billion. The authors mentioned that investing is typically used for technical development, marketing, and international expansion. Rosenberg (2020) states that in 2019, Spotify made an operating profit with total revenue of $8.28 billion.

Spotify's profitability, a great example of scale economics, depends mainly on increasing active users. It's worth noting that the premium user makes the most profit despite the additional ad revenue that free version users bring in. Statista (2023) reports that premium users account for about 40% of all Spotify users. The table below shows the number of free and premium Spotify users from 2015 to 2023.

Table 5. Spotify Users Number over time

Year	**Users (mm)**
2015	91
2016	123
2017	160
2018	207
2019	271
2020	345
2021	406
2022	489
2023	602

Source: Adapted from Statista (2024).

Despite Spotify's growing business success, some musicians have conflicting opinions about the company. Gierhart (2019) claims that Spotify received the first wide criticism in 2009 when Lady Gaga received just 167 dollars for one mln streams of her single Poker Face. The same author argues that in 2014, Taylor Swift removed her music catalog from Spotify, saying that music is a form of art and should be paid for. Such negative feedback from the artists has its objective reasons. Eggers (2018) states that most streaming services cheat the artists. For instance, Spotify pays approximately 0,0038 dollars per stream. Artists could receive much higher revenue than digital and physical albums, obtaining a certain percentage from each sale. However, there is another, even more significant financial issue. According to Rosenberg (2020), artists do not receive payments directly from Spotify. Usually, Spotify pays big labels directly, which receives 50 to 85 percent of the overall payout, and then big labels share the remaining piece of the pie with artists. Thus, payments go through several parties, significantly reducing the musicians' earnings.

Contrary to this, Spotify's well-thought-out recommendation system allows artists and musicians to gain more plays, which means more earnings. Spotify's recommendation algorithms are a critical competitive advantage among music streaming services. It is worth noting that another company initially adopted this technology. According to Razlogova (2020), Echo Nest is an advanced algorithmic recommendation engine founded in 2005 and sold to Spotify in 2014. Therefore, this technology is an additional financial tool for increasing the overall number of songs played and further using the software. Reichert (2019) claims that more than 30% of Spotify's content consumption results from the recommendation system. Although these algorithms significantly help artists increase the number of played songs, Spotify publishes many compositions daily, and many of them never find their listeners, creating a paradox of choice for the listeners. Thousands of tracks are added to Spotify daily, more than anyone could listen to in a lifetime (Anbuhl, 2018). Eriksson et al. (2019) argue that around 20 percent of music content on Spotify has yet to be heard.

Nevertheless, Hargrave (2018) argues that a new exclusive agreement allowed musicians to release albums to premium subscribers. It benefited artists who had contracts with Universal Music Group and Merlin. Ultimately, it helped artists receive better compensation for their music. Also, Spotify constantly tries to invent exclusive features primarily valuable to artists and subscribers. Witt (2019) states that many features, such as playlists, merchandise pages, weekly playlists, and concert date information, help artists generate an additional revenue stream.

Indeed, playlists can be curated by users or generated by specialized algorithms that cater to various musical tastes by closely analyzing listeners' preferences. According to Prey (2019), playlists play a considerable role in music streaming services. Users create more than three billion different playlists, and Spotify creates more than 4.5 thousand playlists. The same author claims that some playlists, such as 'Discover Weekly,' 'Daily Mix,' 'Release Radar' and 'Your Summer Rewind' are generated automatically depending on user taste. Other than that, some playlists, such as 'RapCaviar' and 'Jazz Classics,' were created by the Spotify team. Hracs and Webster (2021) mentioned that playlists help users overcome choice overload.

Furthermore, Spotify developers have always worked to involve musicians and users by adding social integration mechanisms. For instance, Lozić and Vojković (2020) argue that Spotify motivates subscribers to register with a Facebook account to make it easier to connect with other users with whom they share similar musical tastes. The same authors mentioned that Spotify perfectly adapts to many operating systems, including Windows, Mac OS, Android, Linux, etc.

With the development of Spotify and the transformation of a Swedish startup into a technology giant, today, the question is asked whether success lies in music and whether Spotify is just a program that distributes legal music. Vonderau (2019) argues that the Spotify platform is not just about music. It connects technology, music, and advertising in one place. As Spotify continues to gain popularity, it has become a phenomenon. Now, it serves as both the subject of scientific research and a model example for small IT companies that would like to repeat the success of the Swedish startup. According to Fleischer (2021), Spotify became a business metaphor frequently used for a business model that could be implemented in different technological variations such as digital movies, literature, etc. Ultimately, Spotify's success can be attributed to a unique idea, an innovative business model, an advanced system of personalized recommendations, and long-term technological innovation that delights millions of Spotify users worldwide to this day.

2.3 Introduction to Technology Acceptance Theories

In the modern world, technology plays a vital role in the life of human activity. They relate to various areas such as academic education, business environment, entertainment, etc. Samaradiwakara et al. (2014) noted that the first use of the word "technology" was found in a Harvard University course on the "Application of the Sciences to the Useful Arts" in 1816.

It is worth noting that the process of creating each technology includes several stages. To satisfy the end consumer, it is necessary not only to produce a specific technology but also to effectively implement and iteratively evaluate the process of “acceptance” of the technology by the end consumer. Taherdoost (2018) claims that the term "acceptance" means positive action from the user to obtain an innovation. In other words, “accepting” is an antagonist of "refusal." Generally, the term "technology acceptance" means the positive reaction of the individual to using a technology.

Samaradiwakara et al. (2014) state that technology acceptance has become more relevant for researchers with the advancement of technology. According to Lai (2017), researchers have tried to understand why individuals accept technologies through different technology acceptance theories for years. From an academic perspective, researchers worldwide have actively begun to develop increasingly refined theories and models of technology acceptance (Alkhwaldi et al., 2017). It is worth noting that the more complex the technology was born, the more complicated the theory of technology adoptions and were required from the methodological approach. Yucel and Gulbahar (2013) write, "The process of individual users’ acceptance or rejection of technology is a complex process which cannot be explained by only one variable."

Rahman et al. (2021) argue that researchers and practitioners are highly interested in opportunities connecting businesses and technologies. Technology acceptance is essential for IT organizations as they use these theories to develop their products and test consumer acceptance and use. Moreover, in a practical sense, technology acceptance theory helps develop new marketing strategies and create consumer-friendly designs. In addition, these frameworks help increase the security of digital products and reduce the potential risks associated with the relevant technology.

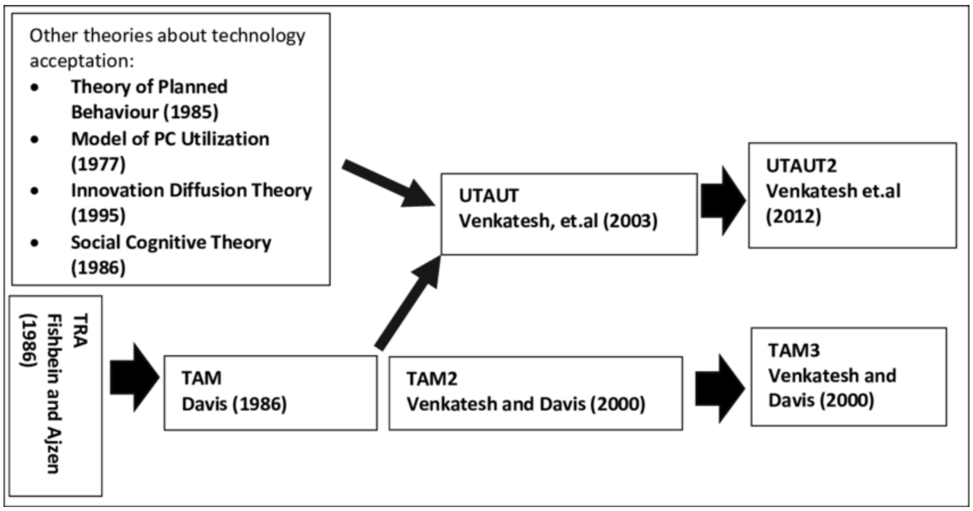
Momani and Jamous (2017) argue that two significant issues exist regarding technology acceptance models. First, each model implements different terms but has a similar concept. Second, due to the difficulty of analyzing behavior and the limitations of the literature, no single holistic approach covers every behavioral aspect. There are also challenges with the emotional component, which can also cause specific bias in the research findings.

Furthermore, to ensure the applicability and adaptability in diverse contexts, theories and models of technology acceptance need to be tested repeatedly on different technologies and people from various sociocultural groups. According to Rahman et al. (2021), although the number of studies focused on technology adoption has dramatically increased, the existing literature contains limited studies analyzing consumer behavior using technology acceptance theories.

2.3.1 Evolution of Technology Acceptance Theories

The evolution of technology acceptance theories perfectly illustrates the dynamics and changing trends in the relationship between humanity and technology. Over time, these models and technologies became increasingly complex and holistic, considering more factors and determinants. With more research in psychology and social sciences, researchers now have more tools to explore more advanced technologies.

Figure 2. Chronological Graph for the Technology Acceptance Theories



Source: Evolution of theories about technology acceptance Source: Rondan-Cataluña, Arenas-Gaitán and Ramírez-Correa (2015).

As shown in Figure 2, technology acceptance theories have different origins and have gone through various stages of development. Alkhwaldi et al. (2017) state that it's essential to understand that technology adoption models have different determinants and different predictive powers with appropriate advantages and drawbacks.

This subsection chronologically examines the main theoretical models of technology acceptance, including their features and limitations.

Theory of Reasoned Action (TRA)

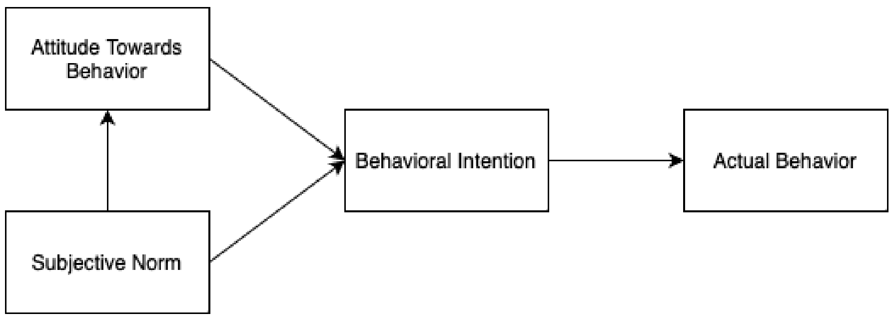
The Theory of Reasoned Action (TRA) was the earliest technology acceptance theory developed by Ajzen and Fishbein in 1975. It is one of the most influential models of human behavior. This model resulted from persuasion models of psychology (Momani & Jamous, 2017).

TRA investigates human behavior via three cognitive aspects: 1) Attitudes, 2) Social Norms, and 3) Intentions. Attitudes refer to "the unfavourableness or favourableness of a person’s feeling for a behavior," Subjective Norms refer to "social pressure," and Intentions refer to "an individual’s decision to do or not do a behavior" (Taherdoost, 2018).

Even though the theory of reasoned action is already outdated, many researchers still use it to study technology adoption, adding various extensions from other theories. For instance, Rausch and Kopplin (2021) use an extended TRA model to determine the primary antecedents of the purchase behavior of sustainable clothing. Another example is Xiao (2020), who examines additional factors that correlate with the behavioral intentions of watching eSports.

Although many researchers are still implementing the Theory of Reasoned Action, it has some limitations in accepting technology. Taherdoost (2018) claims that the Theory of Reasoned Action doesn't consider an individual's habits and moral factors.

Figure 3. Theory of Reasoned Action



Source: Adapted from Ajzen & Fishbein (1975).

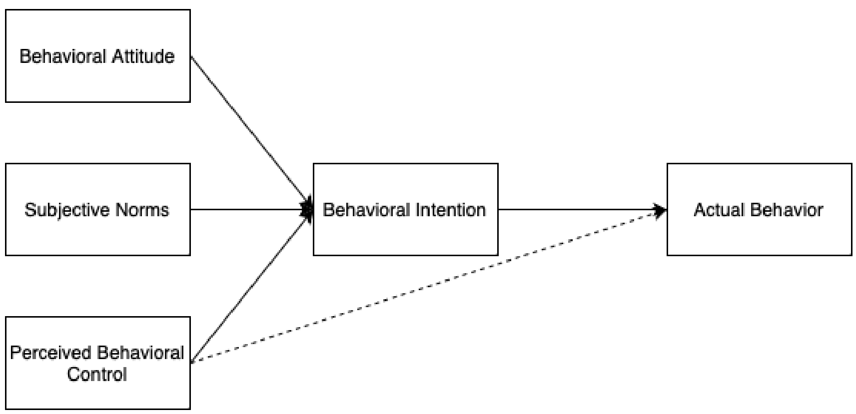
Theory of Planned Behavior (TPB)

Ajzen (1991) developed the theory of planned behavior (TPB) in an article called "The Theory of Planned Behavior" in the journal Organizational Behavior and Human Decision Processes.

This model extended the Theory of Reasoned Action, adding a new construct called behavioral control. Behavioral control in this theoretical model refers to the perceived difficulty of performing an individual behavior. TRA and TPB are quite similar models in that they don't assume a specific human behavior. In other words, they expected rational decision-making (Li, 2010).

Like the preceding model, the Theory of Planned Behavior is not without its set of limitations. According to Alkhwaldi et al. (2017), the Theory of Planned Behaviour ignores individuals' demographic constructs, which can potentially lead to biases. Rahman et al. (2021) claim that "TPB did not explain the mechanism of the individual and how it is related to the model." Momani & Jamous (2017) also mentioned that TPB doesn't consider the economic and environmental aspects that can influence human behavior.

Figure 4. Theory of Planned Behavior



Source: Adapted from Ajzen (1991).

Technology Acceptance Model (TAM)

Davis (1989) developed the Technology Acceptance Model. He published the final version of his study, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," at the University of Michigan.

TAM is built upon a theoretical model called the Theory of Reasoned Action (TRA). Unlike TRA, TAM focuses on perspectives rather than considering external opinions. It evaluates two main factors: a technology's perceived usefulness and ease of use (Alomary and Woolard, 2015).

- Perceived Usefulness is the degree to which an individual believes using a system will improve performance (Davis, 1989).
- Perceived ease of use is the degree to which an individual believes that using a given information system requires little effort (Davis, 1989).

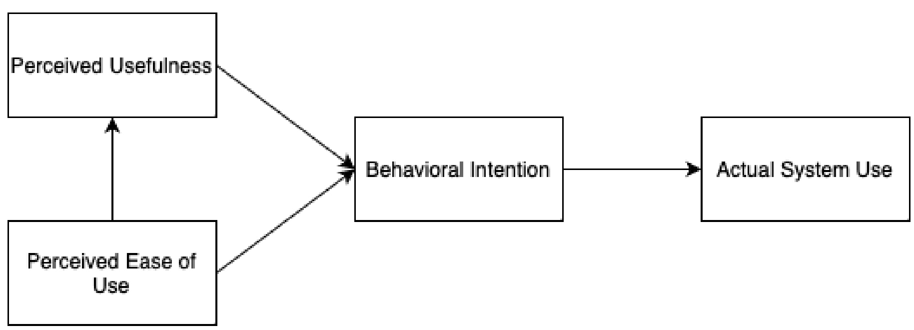
Almehmadi (2020) mentioned that this model is the most used technology acceptance model for information systems and technology adoption. According to Samaradiwakara et al. (2014), the Technology Acceptance Model is more accessible than most other theoretical frameworks and provides an inexpensive way of receiving information about an individual's perception. Wibowo (2019) states that the Technology Acceptance Model met two main objectives. First, it gives new theoretical insights into understanding human behavior in the context of technological adoption. Secondly, practical testing provides a new theory for system designers to evaluate their information technology.

The Technology Acceptance Model (TAM) has seen several significant extensions, which are more foundational and widespread than those found in other technology acceptance models. Rahman et al. (2021) noted that Davis and Venkatesh elaborated on the extension of TAM and called it TAM2 in 2000. This model mainly focused on perceived usefulness and behavioral intention, adding new constructs such as 1) Social influence and 2) Cognitive instrumental processes. Social influences include subjective norms and image, while cognitive instrumental processes include job relevance, output quality, result demonstrability, and perceived ease of use.

Subsequently, Venkatesh and Bala published a new extension of the Technology Acceptance Model, TAM3, in 2008. TAM3 included new characteristics such as Individual Differences, System Characteristics, Social Influence, and Facilitating Conditions. TAM 3 combines the previous two models with a more comprehensive understanding of usage behavior and adoption (Wibowo, 2019).

Although many researchers commonly use the Technology Acceptance Model, it has limitations, like other models, in accepting technology. According to Almehmadi (2020), some factors, like perceived awareness, perceived quality of systems, perceived security, perceived privacy, and perceived trust, are not resolved within this framework.

Figure 5. Technology Acceptance Model



Source: Adapted from Davis (1989).

Social Cognitive Theory (SCT)

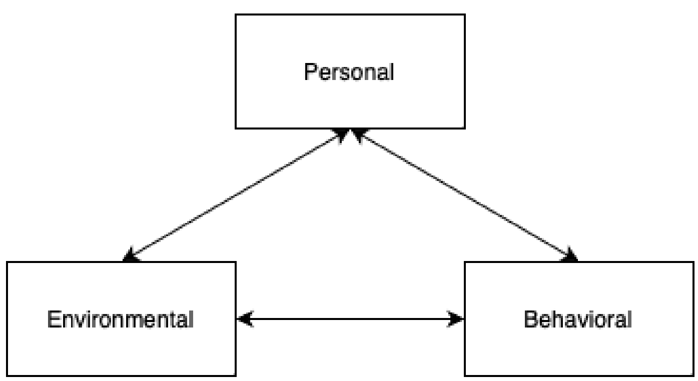
The Social Cognitive Theory draws its approach from social psychology and social learning theory, initially developed as early as 1941. Bandura (1986) developed Social

Cognitive Theory (SCT) and introduced it in his book, "Social Foundations of Thought and Action."

Bandura (1986) mentioned that this model has three significant factors: 1) Personal, 2) Environmental, and 3) Behavioral. Taherdoost (2018) claims that the Social Cognitive Theory represents a triadic model in which each factor influences another. In other words, this model emphasizes the importance of observing cognitive processes in human behavior. SCT focuses on how people control themselves and stay motivated to achieve specific goals over time.

When applying Social Cognitive Theory, there are several significant limitations to consider: According to Momani & Jamous (2017), the Social Cognitive Theory doesn't focus on technology acceptance or motivation. Moreover, it's unclear which factor has more influence than another.

Figure 6. Social Cognitive Theory



Source: Adapted from Bandura (1986).

Innovation Diffusion Theory (IDT)

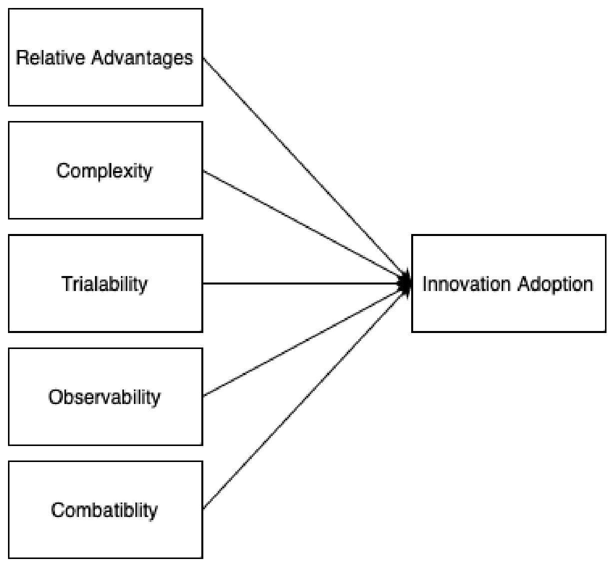
Rogers (1962) developed the innovation diffusion theory and published it in his "Diffusion of Innovation" study, which represented how ideas and innovations are accepted by behavioral intention.

According to Rogers (1962), this model has five significant determinants influencing the adoption of an innovation: 1) relative advantages, which shows that the innovation is better than the technology the individual has previously used); 2) complexity shows whether the technology is easy or difficult to use); 3) trialability shows that the technology was tested before adoption; 4) observability shows the observed benefits from innovation; and 5) compatibility shows whether the innovation fits with the technology used.

Momani & Jamous (2017) claim that the Innovation Diffusion Theory is one of the oldest diffusion models, which was the outcome of several diffusion investigations and focused on technological innovativeness.

It is worth noting that the innovation diffusion theory has some weaknesses in terms of practical application. Rahman et al. (2021) state that "the innovation diffusion theory did not mention how attitudes affect the decision of acceptance and rejection, meaning how the innovation influences the decision. This can summarise that this theory does not care about individual resources or social aid for new behaviors." Taherdoost (2018) claims that the innovation diffusion theory has less predictive and explanatory power than other technology acceptance theories.

Figure 7. Innovation Diffusion Theory



Source: Adapted from Rogers (1962).

Motivational Model (MM)

Davis, Bagozzi, and Warshaw developed the Motivational Model in 1992.
According to Alomary and Woolard (2015), the motivational model is based on the psychological factors of technology acceptance. The same authors claim that human behavior is based on two motivations: 1) Intrinsic and 2) Extrinsic. Intrinsic motivation arises from a person's internal desire to complete a task, while extrinsic motivation occurs when the cause of motivation is outside.

Like previous models, the motivational model has its drawbacks. According to Alkhwaldi et al. (2017), although the motivational model has been widely used in the context of technology acceptance, it represented a comparatively low percentage of the variance in behavioral intention.

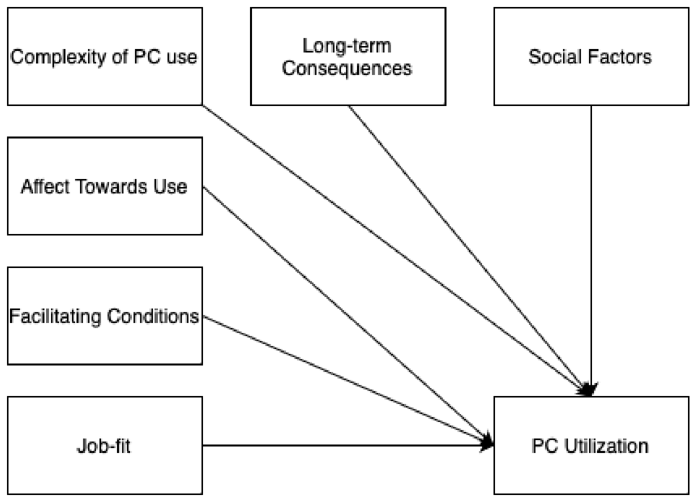
Model of PC Utilization (MPCU)

Thompson et al. (1991) developed the PC utilization model and published it in the study "Personal Computing: Toward a Conceptual Model of Utilization." Thompson et al. (1991) modified and adapted a previously known theory about interpersonal behavior by Triandis, who developed it in 1977.

Thompson et al. (1991) state that the Model of PC utilization has six constructs, which are: 1) Job-fit, 2) Complexity, 3) Long-term consequences, 4) Affect Towards Use, 5) Social Factors, and 6) Facilitating Conditions. Simply put, this model ensures that an individual gets the maximum benefit from using a personal computer. The MPCU theory proposes that factors influence how much an employee utilizes a computer. These include their affinity for using computers, the established norms within their workplace regarding computer usage, their familiarity with using computers, their outcomes when using them, and the level of support they receive at work.

Like several previously mentioned technology acceptance theories, this model is rather broad in application to specific research issues. Taherdoost (2018) noted that Affect and Facilitating Conditions are not considerable constructs in this context due to the low effect on PC use. Furthermore, the behavior construct was excluded from this model. Rahman et al. (2021) argue that "the MPCU theory did not explain the complexity and indirect impact on perceived short-term consequences."

Figure 8. Model of PC Utilization



Source: Adapted from Thompson et al. (1991).

The Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al. (2003) introduced the Unified Theory of Acceptance and Use of Technology model in their study called "User Acceptance of Information Technology: Toward a Unified View."

UTAUT model combines eight previous theories and models of acceptance technology: 1) Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975), 2) Theory of Planned Behavior (TPB) (Ajzen, 1985), 3) Innovation Diffusion Theory (IDT) (Rogers, 1962), 4) Social Cognitive Theory (SCT) (Bandura, 1986), 5) Motivational Model (MM), 6)

Combined TAM and TPB Model, 7) Model of PC Utilization (Thompson et al., 1991), 8) Technology Acceptance Model (TAM) (Davis, 1989).

According to Venkatesh et al. (2003), there are four primary independent constructs in the UTAUT model: 1) Performance Expectancy (PE), 2) Effort Expectancy (EE), 3) Social Influence (SI), 4) Facilitating Conditions (FC). Additionally, four moderators influence variables: 1) Gender, 2) Age, 3) Experience, and 4) Voluntariness of use.

Each separate construct helps to observe how much people are likely to use a particular technology:

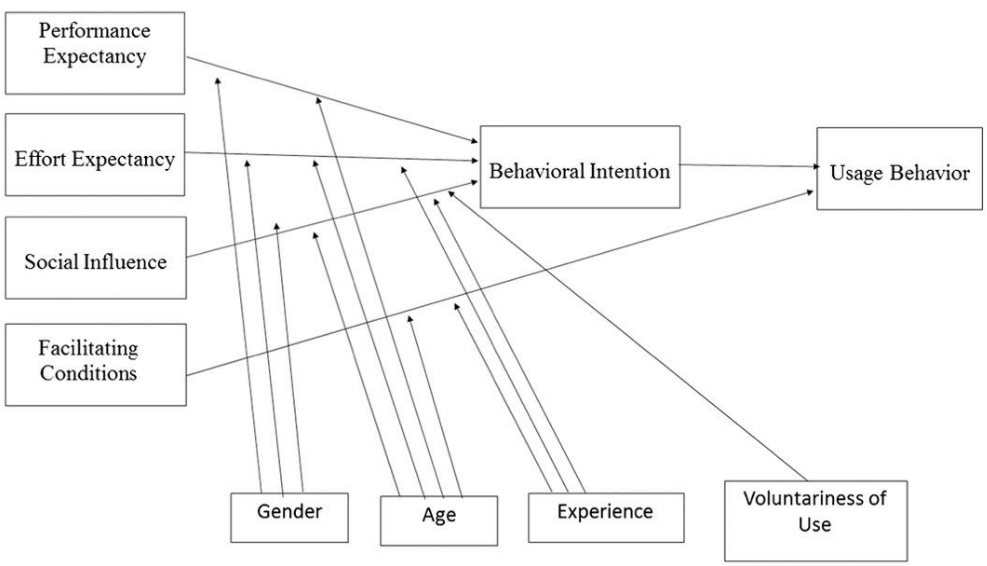
- Performance Expectancy (PE): “the degree to which people believe that the use of technology will improve the functionality of their work” (Almehmadi, 2020).
- Effort Expectancy (EE): “the degree to which people believe that the use of technology to perform their work will be easy” (Almehmadi, 2020).
- Social influence (SI): “the degree to which one believes that others believe that he or she needs to use technology” (Almehmadi, 2020).
- Facilitating conditions (FC): “the degree to which people believe that the infrastructure necessary to support their use of technology is available and accessible” (Almehmadi, 2020).

Four main factors moderated the proposed constructs: 1) Gender, 2) Age, 3) Experience, and 4) Voluntariness of Use.

Notably, theories originating from psychology and sociology center on the behavioral aspects of technology acceptance, while those emerging from IT are more concerned with systems' attributes and how they influence technology acceptance.

According to Talukder et al. (2020), even though the UTAUT model shows comprehensive outcomes for evaluating technology adoption and use, it still has several limitations, such as mandatory and organization settings, which were overcome by Venkatesh et al. (2012), adding Price Value, Hedonic Motivation, and Habit. These constructs helped to overcome those limitations.

Figure 9. The Unified Theory of Acceptance and Use of Technology



Source: Khechine, H., Lakhal, S., & Ndjambou, P. (2016). A meta-analysis of the UTAUT model: Eleven years later.

Unified Theory of Acceptance and Use of Technology 2

Continuing the previous subsection, it is essential to review the most updated and comprehensive technology acceptance theory used in this study as a theoretical construct called UTAUT2 (Figure 1). The Unified Theory of Acceptance and Use of Technology 2 is an advanced theoretical model that aims to understand user adoption and use of technology in different contexts. Venkatesh et al. developed the UTAUT2 model in 2012. They published it initially in their study, "Consumer Acceptance and Use of Information Technology: extending the Unified Theory of Acceptance and Use of Technology."

Raditya (2022) mentioned that the extended version of UTAUT, which is UTAUT2, added three new constructs: 1) Hedonic Motivations, 2) Price Value, and 3) Habit. Other than that, the voluntariness of use has been removed, reducing four moderators to three.

- Hedonic Motivation (HM): “is defined as the fun or pleasure derived from using a technology” (Venkatesh et al., 2012).
- Price Value (PV) is the degree to which users reasonably perceive the information system's cost (Venkatesh et al., 2012).
- Habit (H) is “the extent to which it reflects the results of prior experiences” (Venkatesh et al., 2012).

Using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) across various contexts is highly recommended by numerous researchers (Rondan-Cataluña et al., 2015). Rahman et al. (2021) claim that UTAUT2 is the most comprehensive theoretical model compared to other adoption models. The authors argue that many researchers confirm this model is much more effective than the previous one in understanding consumers' adoption and acceptance of technologies. Tamilmani et al. (2021) suggest using the UTAUT2 model to conceptualize a new way of investigating technology adoption. Chang (2012) mentioned that the UTAUT2 framework improves the variance in behavioral intention from 56 percent to 74 percent and technology use from 40 percent to 52 percent.

In addition, many researchers confirm the effectiveness of this model even with a small sample of respondents, which makes it possible to process data for specific segments and niche products. For example, Satama (2014) had a sample size of 124 participants employing the UTAUT2 model in analyzing AirBnB. Another example is Mahfuz and Khanam (2017), who investigated mobile banking service adoption through UTAUT2 and had 115 valid participants in their study.

Venkatesh et al. (2012) suggest testing UTAUT2 in different countries, age groups, and technologies, which helps to improve the applicability of this model in the context of technology adoption. Despite its short history, this framework is widely used in various academic research worldwide and diverse technological spheres. Unified Theory of Acceptance and Use of Technology 2 was applied in the context of artificial intelligence (Cabrera-Sánchez et al., 2021); software-as-a-service (Lindgren, 2015); internet-of-things (Kessler & Martin, 2017); Virtual Reality (Figliozzi, 2018); blockchain technology (Dollo, 2023); Podcasts (Grett & Jakobs, 2021); mobile banking services (Gharaibeh et al., 2018), etc. Although the study of Venkatesh et al. (2012) was published comparatively recently in 2012, it had already received more than 16,000 citations in Google Scholar by 2023.

While limited research exists on adopting music streaming services using the Unified Theory of Acceptance and Use of Technology 2, several significant studies contribute to this context. The proposed literature is organized in chronological order.

Table 6. UTAUT2 Model Studies on Music Streaming Adoption

Author	Region	Research Objective
Martins (2013)	Portugal	Investigated the adoption of online music streaming users.
Helkkula (2016)	Finland	Researched consumers' intention to subscribe to music streaming services.
Maksim (2018)	Russia	Analyzed the drivers impacting the acceptance of streaming services.
Walean and Rachmawati (2018)	Indonesia	Analyzed the adoption of Spotify and JOOX applications.
Chandra et al. (2018)	Indonesia	Investigated the factors influencing the intention of the Spotify application.
Amalina (2019)	Indonesia	Proposed a marketing strategy for Spotify by analyzing the behavioral

		intentions of free and premium users.
Park (2020)	South Korea	Analyzed the factors affecting customers' intention to use music streaming services.
Barata and Coelho (2021)	Portugal	Analyzed which factors influence the intention to purchase a music streaming service and its recommendation.
Suhod et al. (2022)	Malaysia	Explore the factors influencing the continuance of Spotify Premium subscriptions.
Barata and Barata (2023)	Portugal	Investigated the factors influencing music consumption via music streaming services.

2.5 Hypotheses Development

Performance Expectancy

Venkatesh et al. (2012) argue that performance expectancy is a significant construct for behavioral intention. It relates to the human perception regarding the benefits of a technology doing particular activities. Performance expectancy means how much people think technology will help them do things better. Some older theories about adopting technology have already been discussed but use slightly different words and arrangements. Venkatesh et al. (2003) claim that performance expectancy is like perceived usefulness from TAM. Walean and Rachmawati (2018) state that performance expectancy in the Spotify context relates to access to substantial legal music content compared with illegal platforms.

Several studies support the positive influence of performance expectancy on behavioral intention in the context of music streaming services. (Park, 2020; Barata and Coelho, 2021; Maksim, 2018).

Observing these statements, the study hypothesizes that:

H1: Performance expectancy positively relates to behavioral intention to use Spotify in Azerbaijan.

Effort Expectancy

Venkatesh et al. (2012) state that effort expectancy is the degree of ease related to individuals' work with technology. Venkatesh et al. (2003) argue that effort expectancy is like perceived ease of use from TAM. To put it in simpler words, it measures how comfortable and convenient customers feel when using a technology. Chandra et al. (2018) claim that if the technology is accessible, it does not take extra effort, and vice versa; if it is complicated, it will. Since many music streaming services offer similar functions, their user-friendliness depends mainly on the design's appearance and how information is organized in the software. Suhod et al. (2022) claim that expectancy relates to the convenience of Spotify usage. Convenience means the ease of usage in this context. According to Walean and Rachmawati (2018), effort expectancy in the Spotify context means receiving a better user experience while using this platform.

Several studies support the positive influence of effort expectancy on behavioral intention in the context of music streaming services (Martins, 2013; Barata and Coelho, 2021).

Observing these statements, the study hypothesizes that:

H2: Effort expectancy positively relates to behavioral intention to use Spotify in Azerbaijan.

Social Influence

Venkatesh et al. (2012) argue that social influence determines family or friends' belief in using technology. People tend to be influenced by the opinions, suggestions, and personal stories of those around them, like friends, family, coworkers, or even online groups. When someone observes others actively using and recommending a technology, they are often inclined to follow suit. Chang (2012) mentioned that social influence is similar to the subjective norm explored in Technology Acceptance Model 2. Chen et al. (2018) claim that social influence refers to "the extent to which people perceive that their peers believe that they should use music streaming services."

Several studies support the positive influence of social influence on behavioral intention in the context of music streaming services (Barata and Barata, 2023; Martins, 2013; Maksim, 2018).

Observing these statements, the study hypothesizes that:

H3: Social influence positively relates to behavioral intention to use Spotify in Azerbaijan.

Facilitating Conditions

Venkatesh et al. (2003) state that facilitating conditions refer to "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system." Having the support and resources to utilize technology is crucial. This involves having someone to assist and give access to the tools. When individuals feel they have these resources, they engage with the technology. Yannick (2023) states that facilitating conditions show whether the listener has adequate resources to consume music through music streaming platforms. Consumers would have difficulties listening to music online without these conditions. In the context of this study, listeners may need appropriate devices such as smartphones, headphones, etc. Furthermore, there are extra benefits, such as linking Spotify accounts to a smart TV or a game console for added convenience.

Several studies support the positive influence of facilitating conditions on behavioral intention in the context of music streaming services (Barata and Barata, 2023; Amalina, 2019; Chandra et al., 2018).

Observing these statements, the study hypothesizes that:

H4: Facilitating conditions positively relate to behavioral intention to use Spotify in Azerbaijan.

Hedonic Motivation

Venkatesh et al. (2012) claim that hedonic motivation determines the level of fun or pleasure an individual has using a particular technology. Chen et al. (2018) argue that music streaming services are a hedonic information system because they create pleasure. According to Suhod et al. (2022), hedonic motivation in the Spotify context means receiving enjoyment from music streaming. Spotify service is considered a hedonic service, as its fundamental purpose is to give listeners pleasure.

Several studies support the positive influence of hedonic motivation on behavioral intention in the context of music-streaming authors (Park, 2020; Helkkula, 2016; Martins, 2013).

Observing these statements, the study hypothesizes that:

H5: Hedonic motivation positively relates to behavioral intention to use Spotify in Azerbaijan.

Price Value

Price value within the Unified Theory of Acceptance and Use of Technology 2 shows the relationship between the user who spent money using the product and the value received. This determinant includes assessing the cost of technology and considering its benefits and effectiveness in solving problems. Venkatesh et al. (2012) argue that the cost and pricing structure considerably impact individuals' technology. Individuals may also compare the cost with alternative music streaming services and evaluate whether they offer a favorable return on investment. Yannick (2023) argues that price value means that music streaming provides good value for money. According to Suhod et al. (2022), price value in the context of Spotify is related to the benefits received from Spotify's premium subscription cost.

Several studies support the positive influence of price value on behavioral intention in the context of music streaming services (Wagner and Hess, 2013; Helkkula, 2016; Chandra et al., 2018).

Observing these statements, the study hypothesizes that:

H6: Price value positively relates to behavioral intention to use Spotify in Azerbaijan.

Habit

According to Venkatesh et al. (2012), habit determines the perceptual feeling that reflects the influence of previous experiences. In simple words, "Habit" means using a tech without thinking much. People stick to a particular technology and find it hard to switch. Habits are formed through repeated use of technology occasionally, which can influence the adoption of technologies. Chang (2012) mentioned that even though the concept of habit proposed by other researchers is similar, there are two different concepts behind it. In the first place, habit represents the previous behavior of the individuals, while the second concept illustrates the automatic behavior of individuals. In this study, the concept of habit is employed to examine the routines of music listeners when using the Spotify software. For example, if a consumer consistently turns to Spotify for their music listening needs, it indicates a habitual behavior associated with using the platform.

The positive influence of habit on behavioral intention in the context of music streaming authors is supported by several studies (Park, 2020; Chandra et al., 2018; Helkkula, 2016).

Observing these statements, the study hypothesizes that:

H7: Habit positively relates to behavioral intention to use Spotify in Azerbaijan.

Behavioral Intention

The behavioral intention in UTAUT2 means whether a person plans to use a technology. Park (2020) claims that the essence underlying user acceptance relates to the link between behavioral and actual intention. Lubis et al. (2023) argue that behavioral intention can show whether the consumer will stay or leave in an organizational context.

Suhod et al. (2022) state that it's essential to understand the reason behind the continued use of the Spotify application so that service providers can provide better service and make it more competitive and sustainable. According to Walean & Rachmawati (2018), behavioral intention is used to evaluate consumers' interest in using the Spotify service. The same authors suggest testing the behavioral intention of music streaming adoption since it had moderate power in their research.

2.6 Summary

Currently, music streaming services play a significant role in the music industry. They offer access to an extensive library of audio content where users can listen to music, create playlists, and share with others. Despite the large number of players in the global music streaming services market, Spotify has a leading position.

Over the past decades, the issue of technology adoption has become increasingly relevant in the era of digitalization. The emergence of new technologies influences the creation and improvement of technology acceptance theories (Rogers, 1962; Fishbein and Ajzen, 1975; Ajzen, 1991; Bandura, 1986; Davis, 1989; Thompson et al., 1991; Venkatesh et al., 2003; Venkatesh et al., 2012). The most comprehensive and current framework that studies the issue of technology adoption is UTAUT2, created by Venkatesh et al. in 2012. Many scholars and practitioners currently recommend the application of this theory (Chang, 2012; Tamilmani et al., 2021; Rahman et al., 2021; Rondan-Cataluña et al., 2015).

UTAUT2 consists of 7 factors (PE, EE, SI, FC, HM, PV, H) that influence the behavioral intentions of information systems users. Several previous studies on music streaming adoption support the positive impact of these factors on BI (Martins, 2013; Helkkula, 2016; Maksim, 2018; Walean and Rachmawati, 2018; Chandra et al., 2018; Amalina, 2019; Park, 2020; Barata and Coelho, 2021; Suhod et al., 2022; Barata and Barata, 2023).

Despite the widespread use of UTAUT2 in various fields of information systems (Cabrera-Sánchez et al., 2021; Lindgren, 2015; Kessler and Martin, 2017; Figliozzi, 2018; Dollo, 2023; Grett and Jakobs, 2021; Gharaibeh et al., 2018), its application in studying Spotify's adoption, remains undisclosed.

Moreover, Venkatesh et al. (2012) suggest testing UTAUT2 in different countries, age groups, and technologies, which will help improve this model's applicability in the context of technology adoption.

Despite the rapid growth of users and the revenue of music streaming services, notably Spotify, in Azerbaijan, there is a significant gap in studying the adoption of this technology (Appendix C).

The next chapter will operationalize constructs and research design. It will also present the methods and data analysis process of the research. Furthermore, the final subsections will provide information on ethical considerations and limitations in research design.

CHAPTER III:

METHODOLOGY

3.1 Operationalization of Theoretical Constructs

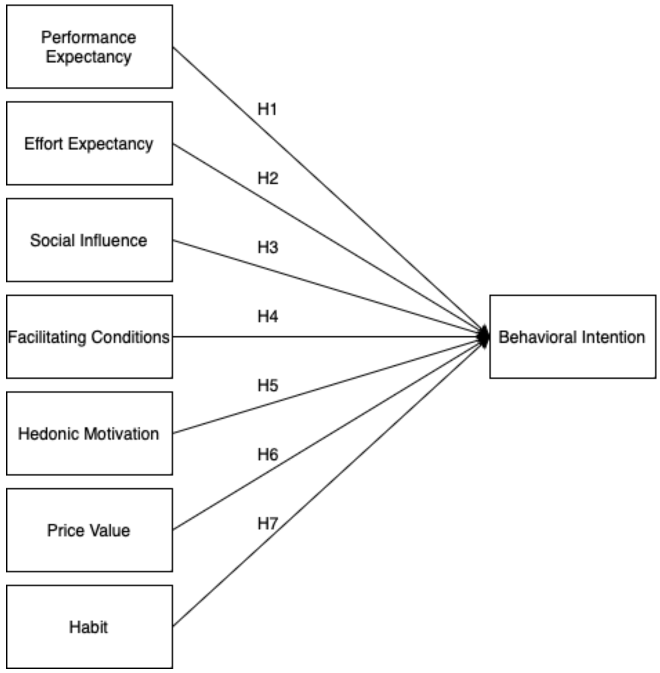
To effectively evaluate the operational construct, it is necessary to demonstrate clear operational definitions, represented in the previous chapter, while forming appropriate hypotheses based on the proposed theoretical framework by studying the adoption and use of Spotify users in Azerbaijan.

This study's theoretical framework will be conducted using UTAUT2, an extension of the UTAUT model, which stands for The Unified Theory of Acceptance and Use of Technology. This model will answer the factors that affect user behavioral intention to use Spotify as a music-streaming platform in the territory of Azerbaijan.

The proposed research model is based on testing seven hypotheses and their influence on behavioral intention (BI) described in the previous subchapter: 1) performance expectancy (PE), 2) effort expectancy (EE), 3) social influence (SI), 4) facilitating conditions (FC), 5) hedonic motivation (HM), 6) price value (PV) and 7) habit (H).

All the proposed hypotheses in this study suggest a positive relationship between the theoretical determinants of UTAUT2 and the adoption of Spotify in Azerbaijan.

Figure 10. Research Model



Source: Adapted from Venkatesh et al. (2012).

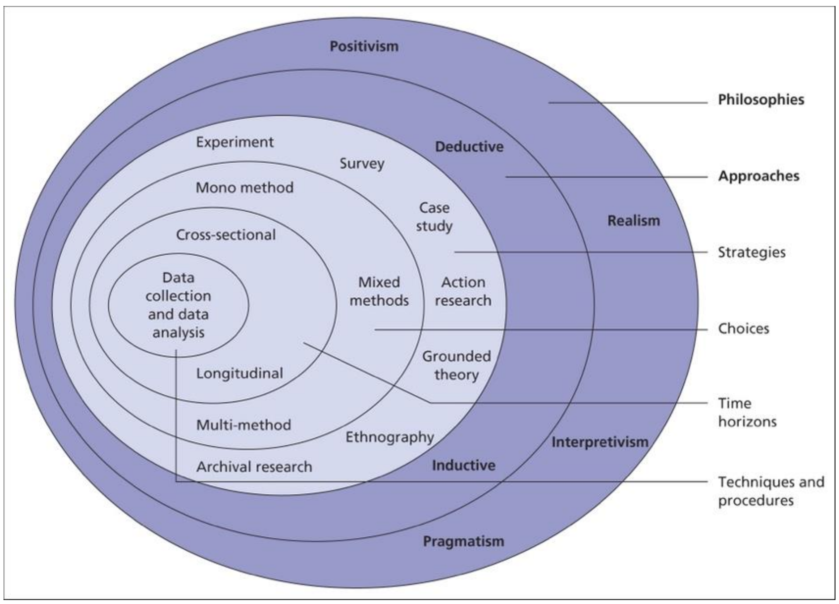
Following Figure 10, the proposed research model of the study illustrates behavioral intention as an endogenous variable positively influenced by seven exogenous latent constructs of the UTAUT2 model.

3.2 Research Design

The study provides the research onion concept proposed by Saunders et al. (2003) for a comprehensive approach to the research design. This approach aims to select and analyze each research design phase, which will consist of different layers.

These layers represent a systematic approach, including philosophy, approach, strategy, methodology, time horizons, techniques, and procedure for collecting research data. Each layer influences the following stages, guiding research design from broad theoretical philosophy to specific practical methods. Raithatha (2017) states that the research onion provides a reasonably comprehensive formulation of the main layers needed to create a constructive methodology.

Figure 11. Research Onion



Source: Robertson, A. (2019). Storytelling for learning in a diagnostic radiography community of practice.

3.2.1 Research Philosophy

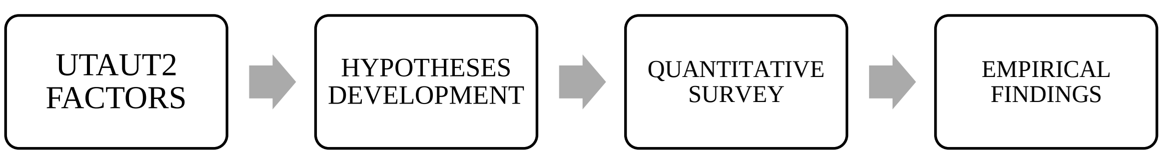
According to Saunders et al. (2003), an influential research methodology is based on a particular philosophical theory that involves research strategies and techniques. Saunders et al. (2003) argue that there is the classical point of view, which has positivist and interpretivism approaches, and two recent research philosophies, pragmatism and critical realism. According to the proposed research philosophies, this study is positivist because it aims to minimize bias, implement empirical methods, and achieve an objective understanding of the factors influencing Spotify's user adoption.

3.2.2 Research Approach

Saunders et al. (2003) claim that there are three types of research approaches: 1) Deductive, 2) Inductive, and 3) Abductive. Since this study aims to test the hypotheses from the ready-made theoretical framework of UTAUT2 and obtain empirical data from users to analyze Spotify, this research can be considered deductive.

The proposed deductive approach consists of four parts. First, the factors of this study's theoretical model, UTAUT 2, are investigated, and then the corresponding hypotheses are formed. Subsequently, these hypotheses are tested by surveying Spotify users in Azerbaijan. Ultimately, the empirical results obtained will help confirm or refute the hypotheses proposed by the research.

Figure 12. Research Approach



3.2.3 Research Strategy

The research onion of Saunders et al. (2003) divides research strategies into the following types: 1) Experiment, 2) Survey, 3) Case Study, 4) Action Research, 5) Grounded

Theory, 6) Ethnography, and 7) Archival Research. Despite this, the proposed research strategies can combine several techniques to form a mixed approach.

The strategy for this study is surveying, as it is an effective strategy for collecting many opinions based on specific behavioral and demographic indicators of Spotify's users in Azerbaijan. According to Ilieva et al. (2001), surveys, particularly web-based surveys, have a considerable advantage because of lower expenses, quick responses, and broader geographical context. In addition, using a survey in this study may help obtain generalizable results that can be reflected in the entire country's population.

3.2.4 Research Method

Generally, research methods are of two types: 1) Quantitative and 2) Qualitative. At the same time, a distinction is made between mono and mixed methods, combining both quantitative and qualitative methods.

This research can be classified as a quantitative method since it uses a quantitative data collection using statistical techniques. Mardiana (2020) states that quantitative methodology is associated with positivist philosophy and a deductive approach. The same author argues that quantitative methodology starts with research questions and is followed by elaborating hypotheses. The empirical findings are associated with two potential answers: whether the hypothesis is accepted or rejected.

3.2.5 Time Horizon

According to Mardiana (2020), the time horizon determines the duration of the study. There are cross-sectional and longitudinal studies, where the first type reveals empirical results for a specific period and the second for an extended period for comparative analysis and identification of more reliable results of the same respondents. Since this study uses a questionnaire that obtains data at one specific moment, this study can be considered cross-sectional.

3.2.6 Data Collection

Considering data collection methods, this study uses primary data collected through a questionnaire. According to Chen and Salmanian (2017), questionnaires refer to a data collection procedure in which participants are asked the same questions in the same order. Saunders et al. (2003) state that quantitative methodology uses questionnaires to obtain required samples for explanatory and descriptive studies. For the convenience of the study, the questionnaire will be conducted entirely online. This questionnaire will be performed using Google Forms. This platform was chosen due to its ease of use and prevalence among similar studies. Primary data will be stored in Microsoft Excel for further processing in statistical tools. The questionnaire includes 29 non-repetitive questions based on the proposed research model.

Table 7. Questions from Questionnaire

Factors	**Items**	**Survey Items**

Performance Expectancy (PE)	PE1	I find Spotify useful in my daily life.
	PE2	Using Spotify helps me accomplish things more quickly.
	PE3	Using Spotify increases my productivity.
Effort Expectancy (EE)	EE1	Learning how to use Spotify is easy for me.
	EE2	My interaction with Spotify is clear and understandable.
	EE3	I find Spotify easy to use.
	EE4	It is easy for me to become skillful at using Spotify.
Social Influence (SI)	SI1	People who are important to me think that I should use Spotify.
	SI2	People who influence my behavior think that I should use Spotify.
	SI3	People whose opinions that I value prefer that I use Spotify.
Facilitating Conditions (FC)	FC1	I have the resources necessary to use Spotify.
	FC2	I have the knowledge necessary to use Spotify.
	FC3	Spotify is compatible with other technologies I use.

	FC4	I can get help from others when I have difficulties using Spotify.
Hedonic Motivation (HM)	HM1	Using Spotify is fun.
	HM2	Using Spotify is enjoyable.
	HM3	Using Spotify is very entertaining.
Price Value(PV)	PV1	Spotify is reasonably priced.
	PV2	Spotify is a good value for the money.
	PV3	At the current price, Spotify provides a good value.
Habit (H)	H1	The use of Spotify has become a habit for me.
	H2	I am addicted to using Spotify.
	H3	I must use Spotify.
Behavioral Intention (BI)	BI1	I intend to continue using Spotify in the future.
	BI2	I will always try to use Spotify in my daily life.
	BI3	I plan to continue to use Spotify frequently

Source: Adapted from (Venkatesh et al., 2012; Amalina, 2019).

In addition to the questions in the table, participants will be asked several demographic questions, including gender, age, and education level, to obtain information about the study sample and develop potential research recommendations (Appendix B).

Likert (1932) suggests using the Likert scale to estimate the participants' behavior and views due to their considerations. Five and seven-point Likert scales are preferred when considering such studies. This study uses a five-point Likert scale, a sample of which is shown in the table below.

Table 8. 5-Point Likert Scale

Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Source: Adapted from Likert (1932).

Since Azerbaijani is the state and most used language in Azerbaijan, all questions and answers were translated from English into Azerbaijani. To validate the questionnaire, all questions were re-translated into English to check the text for grammatical and semantic errors. No considerable differences were found, so it was concluded that the questionnaire was translated correctly.

Before data collection, a pilot questionnaire with a small sample of 20 respondents will assess the research items and their comprehensiveness. Chen and Salmanian (2017) suggest that the pilot study could solve misunderstandings before data collection. Based on the opinion of respondents, if necessary, certain amendments will be made to the questionnaire to validate the analysis. Primary data from respondents from the questionnaire were collected in April 2024. The questionnaire was distributed through several channels, such as LinkedIn, Facebook, and Word of Mouth. All respondents received detailed information about the questionnaire before the beginning. Before the questionnaire began, participants were provided detailed information by the participant consent form added in Appendix A.

3.2.7 Sampling Technique

According to Chen and Salmanian (2017), samples provide benefits such as lowering expenses and reducing the time required to obtain primary data, increasing data reliability and research effectiveness. In analyzing the Spotify adoption in Azerbaijan using the proposed research model, a careful sampling strategy is crucial to ensure the validity and reliability of the research findings. It is worth noting that this study's population includes users of both the free and paid versions of Spotify in Azerbaijan. Since official sources do not provide data on the number of Spotify users in Azerbaijan, a non-probability sampling technique is relevant.

Hair et al. (2011) propose measuring the minimum sample size for PLS-SEM, which should be at least "ten times the largest number of structural paths directed at a particular latent construct in the structural model." Considering the number of paths is 7, the minimum sample size should be at least 70. Therefore, the number of participants in this study was 115. Although the sample size appears small, it is enough to create a structural equation model analysis (Park, 2020).

Moreover, this study used the convenience sampling technique. Participants were chosen based on their availability to participate in this study. In addition, this study uses the snowball sampling technique, where current participants in the survey refer other potential participants to participate.

3.2.8 Data Analysis

To conduct a reliable data analysis, the quality of the primary data collected from respondents must be verified. First, the unnecessary data must be cleared, and then needless outliers must be removed.

The next stage is descriptive analysis, which shows the demographic indicators of the survey participants. After describing and identifying each survey item's average values, standard deviation, minimum, and maximum, relevant measurement and structural models must be prepared.

The data analysis method implemented for the research is a two-step structural equation modeling (SEM). Chin (2000) states that Structural Equation Modeling (SEM) represents an approach that holistically combines diverse portions of the research process. Gefen et al. (2000) claim that Structural Equation Modeling is a multivariate technique implementing aspects of multiple regression and factor analysis to estimate a series of interrelated dependence relationships simultaneously. The first step of SEM is to create an adequate measurement model with a confirmatory factor analysis (CFA). Confirmatory factor analysis will help evaluate the reliability and validity of the constructs in this study. The second step is to create a structural model implementation, which will help assess the relationship between variables and test hypotheses. For appropriate data processing to develop a measurement and structural model, SmartPLS 4 software was chosen for this study.

Chin (1998) suggests using The Partial Least Squares path model approach to SEM to test the proposed hypotheses. The same author justifies the Partial Least Squares approach by two components. First, it works well with a relatively small sample size. Second, it can easily accommodate both reflective and formative scales. Subsequently, interpreting the data will allow understanding the strength and direction of relationships between constructs.

3.3 Reliability & Validity

This study uses various methods of reliability and validity to emphasize the quality of the primary data acquired through a questionnaire.

According to Sürücü and Maslakçi (2020), reliability refers to the consistency of the measured values. In other words, the results will be the same if values are measured multiple times by implementing the same instruments. This study uses two statistical techniques actively implemented in structural equation modeling (SEM): 1) Cronbach's alpha and 2) The composite reliability method.

On the other hand, this study uses several statistical methods to test the validity of the primary data. Validity in the study of Sürücü and Maslakçi (2020) means whether a measurement instrument corresponds to the behavior or quality being measured for which it is intended and indicates how well the instrument represents its function. To ensure content validity, all survey items were taken from the relevant sources of the theoretical construct used in this study, and the questions were adapted to the context of this research. The outer loadings and the Average Variance Expected (AVE) are used for convergent validity. This study uses the Fornell-Larcker criterion and Heterotrait-Monotrait Ratio (HTMT) ratio for discriminant validity.

Considering these statistical reliability and validity methods, the study increases the credibility of the empirical findings and enhances confidence in their accuracy.

3.4 Ethical Considerations

Arifin (2018) states that protecting research participants through implementing relevant ethical principles is significant in every research investigation. Following ethical principles, this study offers all survey participants a digital participant consent form that provides detailed information about the researcher, the purpose of the study, anonymity, confidentiality, benefits, and risks. This form was initially written in English and later translated into Azerbaijani for the understanding and convenience of respondents.

3.5 Research Design Limitation

Despite the numerous methodological advantages of this study, the research design has two main limitations.

First, although the sample size exceeds the minimum requested, compared to some studies in music streaming services adoption, it seems relatively small, which may affect the generalizability of the study's empirical results.

Secondly, although this study implements all the determinants from the theoretical construct of UTAUT2, it omits moderators examining age, gender, experience, and use behavior.

3.6 Conclusion

This chapter describes the research model and provides a detailed and coherent description of the design of this study. Using quantitative methodology, this study uses the survey to collect primary data from Spotify users living in Azerbaijan. In the subsequent chapter, the obtained data will be demonstrated in detail, and the measurement and structural model will be created through SmartPLS 4 software.

CHAPTER IV:

RESULTS

4.1 Descriptive Statistics

This subsection analyzes the descriptive statistics of the surveyed respondents observing active users of the Spotify music streaming service in Azerbaijan. Larson (2006) states that "data analysis begins with calculating descriptive statistics for the research variables."

First of all, it is worth noting that the final number of valid respondents was 115. Each respondent at the time of completing the survey was already an active user of Spotify. Moreover, each respondent confirmed that they had read the Participant Consent Form before starting the questionnaire (Appendix A).

Table 9 below represents the demographic profile of the respondents, including gender, age, and highest level of education completed.

Table 9. Demographic Characteristics

Measurement	Value	Frequency	Percentage
Gender	Male	45	39%
	Female	70	61%
Age	<18	3	3%

	18-25	64	56%
	26-40	45	39%
	41-55	1	1%
	>56	2	2%
Education	High School or Less	6	5%
	College	3	3%
	Bachelor's Degree	72	63%
	Master's Degree	33	29%
	Doctorate Degree	1	1%

Table 9 shows that the participants were almost equally divided between men and women, with 45 males, or 39%, and 70 females, or 61%, respectively.

In terms of age, as expected, most were the young generation who more actively use digital products, notably Spotify (Table 2). Therefore, 3 people, or 3% of the participants, were under 18 years old; 64 people, or 56%, were from 18 to 25 years old; 45 people, or 39%, were from 26 to 40 years old; 1 person, or 1%, were from 41 to 55 years old; and finally, only 2 people, or 2% of the total number of participants, were over 56 years old.

The majority of survey participants were bachelors, 72 or 63%. People who completed a master's degree were 33 or 29%, high school was 6 or 5%, college was 3 or 3%, and finally, only one survey participant graduated from doctoral studies.

In addition to the participant's demographic information, the study provides the mean, median, standard deviation, minimum, and maximum for each survey item of the questionnaire used in this investigation.

Table 10. Descriptive Statistics

Variables	Mean	Median	Standard Deviation	Minimum	Maximum
PE1	3.991	4.000	1.000	1.000	5.000
PE2	3.470	4.000	1.204	1.000	5.000
PE3	3.443	4.000	1.196	1.000	5.000
EE1	4.287	5.000	1.028	1.000	5.000
EE2	4.174	4.000	0.944	1.000	5.000
EE3	4.313	5.000	0.908	1.000	5.000
EE4	4.209	5.000	0.965	1.000	5.000
SI1	3.122	3.000	1.195	1.000	5.000
SI2	3.017	3.000	1.272	1.000	5.000
SI3	3.400	3.000	1.222	1.000	5.000
FC1	4.209	4.000	0.899	1.000	5.000
FC2	4.357	5.000	0.826	2.000	5.000

FC3	4.052	4.000	0.994	1.000	5.000
FC4	3.835	4.000	1.201	1.000	5.000
HM1	4.174	4.000	0.944	2.000	5.000
HM2	4.252	5.000	0.893	2.000	5.000
HM3	4.061	4.000	1.015	1.000	5.000
PV1	3.461	4.000	1.113	1.000	5.000
PV2	3.643	4.000	1.065	1.000	5.000
PV3	3.670	4.000	1.069	1.000	5.000
H1	3.652	4.000	1.230	1.000	5.000
H2	2.896	3.000	1.328	1.000	5.000
H3	3.287	3.000	1.242	1.000	5.000
BI1	3.922	4.000	0.988	1.000	5.000
BI2	3.652	4.000	1.127	1.000	5.000
BI3	3.817	4.000	1.100	1.000	5.000

Based on the fact that the survey consisted of a 5-point Likert scale, the minimum value was one, and, accordingly, the maximum was five. The median ranged from 3 to 5, while the average value ranged from 2.896 to 4.357, which indicates that survey participants, on average, chose a value above average. Finally, the standard deviation values ranged from 0.826 to 1.

4.2 Measurement Model Analysis

The first step in implementing structural equation modeling is constructing a measurement model with a confirmatory factor analysis (CFA). Confirmatory factor analysis is a widely used statistical technique implemented in PLS-SEM to test the fit of the proposed measurement model.

To measure reliability, Cronbach's alpha of the research model's constructs is proposed. Gefen et al. (2000) state that Cronbach's alpha is a widely used measure of reliability for a set of two or more constructs. Values can range from 0 to 1. Higher values indicate higher reliability of the scores. Each value must be greater than 0.70.

Table 11. Reliability testing using Cronbach's Alpha

Constructs	Cronbach's Alpha
Performance Expectancy (PE)	0.867
Effort Expectancy (EE)	0.897
Social Influence (SI)	0.895
Facilitating Conditions (FC)	0.848
Hedonic Motivation (HM)	0.926
Price Value (PV)	0.928
Habit (H)	0.885
Behavioral Intention (BI)	0.931

Following Table 11, all indicators in Cronbach’s alpha exceed the minimum threshold of 0.7. The range of construct values varied from 0.848 to 0.931, which indicates a high level of Cronbach’s alpha indicators of the research model. Therefore, all constructs of the research model passed the first reliability assessment.

Although Cronbach's alpha is the most used method for testing the reliability of constructs, in the context of PLS-SEM, a more comprehensive method called composite reliability is also predominantly used for evaluating the internal consistency of determinants.

Table 12. Reliability testing using Composite Reliability

Constructs	Composite Reliability
Performance Expectancy (PE)	0.919
Effort Expectancy (EE)	0.928
Social Influence (SI)	0.935
Facilitating Conditions (FC)	0.899
Hedonic Motivation (HM)	0.953
Price Value (PV)	0.954
Habit (H)	0.929
Behavioral Intention (BI)	0.956

According to Table 12, all indicators in composite reliability exceed the minimum threshold of 0.7. The range of construct values varied from 0.899 to 0.956, which indicates a high level of composite reliability of the research model. Therefore, all constructs of the research model passed the second reliability assessment. The next step is to assess the validity of the research model.

Hair et al. (2011) state that this study must evaluate outer loadings for convergent validity, where each survey item should be higher than 0.70.

Table 13. Convergent Validity testing using Outer Loadings

Survey Item	Outer Loadings
Performance Expectancy 1	0.858
Performance Expectancy 2	0.923
Performance Expectancy 3	0.884
Effort Expectancy 1	0.863
Effort Expectancy 2	0.861
Effort Expectancy 3	0.910
Effort Expectancy 4	0.861
Social Influence 1	0.925
Social Influence 2	0.934
Social Influence 3	0.867

Facilitating Conditions 1	0.867
Facilitating Conditions 2	0.919
Facilitating Conditions 3	0.794
Facilitating Conditions 4	0.733
Hedonic Motivation 1	0.942
Hedonic Motivation 2	0.945
Hedonic Motivation 3	0.914
Price Value 1	0.919
Price Value 2	0.940
Price Value 3	0.946
Habit 1	0.880
Habit 2	0.919
Habit 3	0.905
Behavioral Intention 1	0.928
Behavioral Intention 2	0.939
Behavioral Intention 3	0.945

According to Table 13, the outer loadings ranged from 0.733 to 0.946 across indicators, indicating a consistently strong relationship between the observed variables and their respective latent constructs in the research model.

Hair et al. (2011) argue that the study needs to assess the average variance extracted (AVE) for convergent validity. For a sufficient level of convergent validity, the average variance extracted should be higher than 0.5, which means that the latent variable explains more than half of its indicators' variance.

Table 14. Convergent Validity testing using AVE

Constructs	Average Variance Extracted
Performance Expectancy (PE)	0.790
Effort Expectancy (EE)	0.764
Social Influence (SI)	0.827
Facilitating Conditions (FC)	0.691
Hedonic Motivation (HM)	0.872
Price Value (PV)	0.875
Habit (H)	0.813
Behavioral Intention (BI)	0.879

Following Table 14, all indicators in Average Variance Extracted (AVE) exceed the minimum threshold of 0.5. The range of AVE values varied from 0.691 to 0.879, indicating a high level of convergent validity for the research model's determinants. Therefore, all constructs of the research model have passed the second convergent validity assessment. The next step is to assess the proposed model's discriminant validity.

This study proposes to evaluate each construct based on the Fornell-Larcker criterion to assess discriminant validity. Henseler (2017) claims, "The Fornell-Larcker criterion maintains that a factor’s AVE should be higher than its squared correlations with all other factors in the model."

Table 15. Discriminant Validity testing using the Fornell-Larcker criterion

	PE	EE	SI	FC	HM	PV	H	BI
PE	0.889							
EE	0.624	0.874						
SI	0.563	0.467	0.909					
FC	0.533	0.721	0.390	0.831				
HM	0.584	0.687	0.423	0.726	0.934			
PV	0.487	0.482	0.404	0.544	0.599	0.935		
H	0.698	0.498	0.598	0.470	0.585	0.539	0.902	
BI	0.768	0.690	0.509	0.569	0.661	0.599	0.816	0.937

Following Table 15, all constructs in the Fornell-Larcker criterion demonstrate that the square root of the Average Variance Extracted (AVE) for each construct is higher than its correlations with other constructs. Therefore, all constructs of the research model have passed the first discriminant validity assessment.

In addition to the widely used Fornell-Larcker criterion for testing discriminant validity, Hair et al. (2019) suggest another method: the heterotrait-monotrait (HTMT) ratio. HTMT is calculated as the average correlation between items across different constructs divided by the average correlation between items within the same construct. A threshold for HTMT.90 criterion of 0.90 is suggested for this measure of validity.

Table 16. Discriminant Validity testing using HTMT ratio

	PE	EE	SI	FC	HM	PV	H	BI
PE								
EE	0.70							
SI	0.63	0.52						
FC	0.62	0.82	0.45					
HM	0.64	0.75	0.46	0.81				
PV	0.54	0.52	0.44	0.61	0.64			
H	0.78	0.55	0.67	0.54	0.64	0.58		
BI	0.84	0.75	0.55	0.64	0.71	0.64	0.89	

According to Table 16, since each construct is less than 0.90, the research model successfully passed the second discriminant validity assessment using the HTMT ratio.

To assess the model fit, the study used the most common criterion for PLS-SEM, the Standardized Root Mean Square Residual (SRMR). The SRMR measures the average standardized errors between the observed and hypothesized correlation matrices. A value less than 0.08 is considered a good fit (Henseler, 2017). Therefore, with the SRMR value of 0.06, the model exhibits a good fit.

This research measures the variance inflation factor (VIF) to verify that there is no high correlation among the independent variables. Hair et al. (2019) claim that "VIF values of 5 or above indicate critical collinearity issues among the indicators of formatively measured constructs."

Table 17. Assessment of Collinearity

Constructs	Variance Inflation Factor (VIF)
Performance Expectancy (PE)	2.520
Effort Expectancy (EE)	2.710
Social Influence (SI)	1.712
Facilitating Conditions (FC)	2.716
Hedonic Motivation (HM)	2.885
Price Value (PV)	1.771
Habit (H)	2.512

Referring to Table 17, all constructs' variance inflation factor (VIF) values indicate no high correlation, with values ranging from 1.712 to 2.885. Consequently, all constructs have successfully passed the collinearity assessment.

4.3 Structural Model Analysis and Hypotheses Testing

After evaluating all the constructs of the proposed research model for reliability and validity, the next step in building structural equation modeling is creating a structural model, which in this context is used to evaluate the significance of the proposed research hypotheses (Henseler, 2017).

Gefen et al. (2000) argue that the structural model represents the connections or dependencies between the variables. One or more dependencies should connect to the model construct.

This study employs the bootstrapping technique for statistical resampling of the original dataset. Specifically, it implements 5000 bootstrap samples generated from the original data.

The coefficient of determination, also known as R^2, is a measure used to evaluate the proportion of the variance in the dependent variable explained by the independent variables. Coefficients of determination (R^2) of 0.75, 0.50, and 0.25 typically indicate substantial, moderate, or weak explanatory power, respectively (Hair et al., 2011). In this study, the model explained 81.1% of the variance in behavioral intention to adopt the

Spotify music streaming service. Therefore, the model can predict a substantive variation of the endogenous variables.

Another measure to evaluate the explanatory power and predictive relevance of the structural model is Q^2. This value must be greater than zero to indicate the predictive accuracy of the structural model for the proposed construct. As a rule, 0, 0.25, and 0.50 values illustrate small, medium, and large predictive relevance in PLS-path models. (Hair et al., 2019). In this study, the model explained 78.2% of the variance in behavioral intention to adopt the Spotify music streaming service. Therefore, the model demonstrates considerable predictive relevance.

This study implements a path coefficient for hypothesis testing, including statistical measures such as p-values and t-values.

In this context, the p-value represents the strength of evidence against the null hypothesis. Using a significance level (α) of 0.05, i.e., 5%, the p-value should be less than 0.05 (Lubis et al., 2023).

Another way to assess the significance against the null hypothesis is to use the t-value. The t-value with a one-tailed test should be greater than 1.645 (Amalia, 2019).

Table 18. Path Coefficients

Hypothesis	Path	β coefficient	T-value	P-value

H1	PE - BI	0.243	3.296	0.000
H2	EE - BI	0.300	3.630	0.000
H3	SI - BI	-0.110	1.899	0.029
H4	FC - BI	-0.064	0.799	0.212
H5	HM - BI	0.039	0.529	0.298
H6	PV - BI	0.119	1.659	0.049
H7	H - BI	0.506	7.015	0.000

According to Table 18, all constructs of the research model except for FC-BI and HM-BI have collected sufficient evidence against the null hypothesis, indicating a statistically significant result.

4.4 Conclusion

Most respondents were relatively young, corresponding to Chandra et al.'s (2018) statement that young people are more likely to use digital products.

Using Confirmatory Factor Analysis (CFA), it was revealed that all constructs of the research model were successfully assessed for various statistical reliability and validity methods. Using the bootstrapping technique, a structural research model was created to evaluate the hypotheses.

Four out of the seven hypotheses (H1, H2, H6, H7) proposed by the study were confirmed, demonstrating statistically significant results with a positive influence on the behavioral intention of Spotify users in Azerbaijan. Only one hypothesis (H3) exhibited a statistically significant result indicating a negative impact on behavioral intention. The remaining two hypotheses (H4, H5) have not collected enough evidence against the null hypothesis and are therefore considered statistically inconclusive for the research.

Table 19. Hypothesis Results

Hypothesis	Path	Results
H1	PE - BI	Accepted
H2	EE - BI	Accepted
H3	SI - BI	Rejected
H4	FC - BI	Rejected
H5	HM - BI	Rejected
H6	PV - BI	Accepted
H7	H - BI	Accepted

CHAPTER V:

DISCUSSION

5.1 Discussion of Results

This chapter interprets each hypothesis analyzed in this investigation, following the supporting literature described in the literature review and results chapter. The results are interpreted based on seven hypotheses, which are positively aimed at studying the behavioral intentions of Spotify users in Azerbaijan.

Performance Expectancy

The analysis highlights that performance expectancy (PE) is an influential determinant, as evidenced by a positive beta of 0.243 ($t = 3.296$; $p = 0.000$). These empirical outcomes highlight the positive impact of performance expectancy on the behavioral intention of Spotify users in Azerbaijan. The performance expectancy in this research consisted of 3 survey items: PE1, PE2, and PE3.

Several studies into the adoption of music streaming services have found similar empirical findings. (Park, 2020; Barata and Coelho, 2021; Maksim, 2018).

Venkatesh et al. (2012) state that performance expectancy is the degree to which technology will benefit consumers in performing certain activities. In this study, several significant factors identify the positive impact of performance expectancy on the behavioral intentions of Spotify listeners.

The most crucial factor is highlighting listeners' primary expectations, expressed by the variety of legal audio content provided by Spotify. As previously mentioned, streaming services, notably Spotify, offer access to a vast library of licensed audio content (Lozic and Vojkovic, 2020), which is a distinct competitive advantage over services offering unlicensed audio content. It is worth considering the fact that competing music streaming services offer similar value propositions. In this case, signing exclusive contracts with labels or local artists and emphasizing the exclusive content provided through relevant marketing channels can create significant opportunities to meet Spotify listeners' expectations and positively influence the user experience in Azerbaijan.

The second important factor is the Spotify recommendation algorithm. It is no secret that the recommendation engine, developed by Echo Nest and later sold to Spotify in 2014 (Razlogova, 2020), is one of Spotify's key competitive advantages. Reichert (2019) mentioned that the recommendation system influences more than 30% of Spotify's content consumption, which indicates the significance of recommendation algorithms in the user engagement of Spotify listeners. Therefore, further technical improvements in the recommendation algorithm will positively increase the performance expectancy of Spotify listeners in Azerbaijan.

Effort Expectancy

The findings highlight that effort expectancy (EE) is an influential determinant, as evidenced by a positive beta of 0.300 ($t = 3.630$; $p = 0.000$). This empirical finding indicates the positive impact of effort expectancy on the behavioral intention of Spotify users in Azerbaijan. The effort expectancy in this research consisted of 4 survey items: EE1, EE2, EE3, and EE4.

The outcomes of this factor align with those of other researchers using the UTAUT2 adoption model in the context of music streaming services (Martins, 2013; Barata and Coelho, 2021).

Venkatesh et al. (2012) claim that effort expectancy is the degree of ease associated with consumers’ use of technology. In this context, several essential factors identify the positive impact of effort expectancy on the behavioral intentions of Spotify listeners.

First, the functionality of music streaming services applications, notably Spotify, has increased significantly in recent years. Increasing functionality can ultimately lead to difficulties in using the technology, especially for inexperienced users. In support of Spotify, it is worth noting that the release and distribution of the Spotify Lite application in some regions has significantly solved this problem. However, in several countries, including Azerbaijan, where music streaming platforms are just gaining popularity, there is a high need for this kind of solution. In addition, a simplified mode for car drivers and adaptation with other platforms, such as Sony PlayStation, makes it easier to use Spotify for listeners in Azerbaijan. Additional technical integrations will help further improve the customer experience and ease of use for Spotify users.

The second considerable factor is playlists. Hracs and Webster (2021) mentioned that playlists help users overcome choice overload. Although playlists simplify the selection of the necessary tracks, their excessive number on the main page can significantly have the opposite effect. It is recommended that the selection of playlists be simplified by developing a more user-friendly interface.

Social Influence

The empirical results regarding the following determinant, social influence (SI), proved unexpected. Despite the positive assessment of ($t = 1.899$) and ($p = 0.029$) values against the null hypothesis, this determinant represented a negative beta coefficient with -0.110. This value proves that the proposed research hypothesis is refuted and states that social influence negatively affects the behavioral intention of Spotify users in Azerbaijan. The social influence in this research consisted of 3 survey items: SI1, SI2, and SI3.

Venkatesh et al. (2012) argue that social influence determines family or friends' belief in using technology. Several studies have shown both insignificant and adverse effects of social influence on the behavioral intentions of music streaming service users. (Suhod et al., 2022; Barata and Coelho, 2021; Chandra et al., 2018).

The main factor for this result can be the difference in taste preferences. For example, the older generation prefers to listen to either old pop or traditional folklore music. In comparison, the relatively younger generation prefers to listen to foreign music, including genres such as rock and hip-hop. The difference in tastes is also accompanied by the cultural and linguistic characteristics of listeners in Azerbaijan. For example, people interested in Turkish culture are predisposed to listening to Turkish music. People oriented toward the English-speaking environment prefer listening to American and European pop and rock stars. For this reason, taste preferences, including the choice of platform that provides different music catalogs for listening to music, are primarily personal and do not depend in any way on the recommendations of the surroundings.

However, several studies have confirmed this factor's positive influence on behavioral intention (Walean and Rachmawati, 2018; Martins, 2013). Therefore, it is recommended that subsequent studies test it on Spotify users in Azerbaijan.

Facilitating Conditions

The first determinant that did not collect sufficient evidence against the null hypothesis was facilitating conditions (FC), with the following values ($t = 0.799$; $p = 0.212$). It's worth noting that these findings haven't interpreted the proposed determinant as positive or negative, as the evidence was inconclusive. Facilitating conditions in this research consisted of four survey items: FC1, FC2, FC3, and FC4.

The results of this factor align with those of other researchers using the UTAUT2 adoption theory in the context of music streaming services (Walean and Rachmawati, 2018; Park, 2020).

Venkatesh et al. (2012) state that the facilitating conditions refer to consumers' perceptions of the resources and support available to perform a behavior. Yannick (2023) mentioned that facilitating conditions show whether the listener has adequate resources to consume music through music streaming platforms. In this study, several essential factors identify the insignificant influence of facilitating conditions on the behavioral intentions of Spotify listeners in Azerbaijan.

One of the main reasons could be the comparatively low technical requirements of music streaming services. In other words, to listen to audio content through Spotify, the user must have only a smartphone and stable access to the Internet. Over the past few years, there has been a significant increase in Internet speed in Azerbaijan, which, at the moment, is no longer a serious barrier to accessing and listening to music through Spotify.

Another factor would be the insufficient sample size, which did not allow the statistical significance of the proposed determinant to be represented. It is worth adding that some studies in the field of the adoption of music streaming services have found a positive relation between facilitating conditions and listeners' behavioral intention (Barata and Barata, 2023; Amalina, 2019; Chandra et al., 2018), which provides a ground for further study of the influence of this factor in the adoption of Spotify in Azerbaijan.

Hedonic Motivation

The second determinant that did not collect sufficient evidence against the null hypothesis was hedonic motivation (HM) with the following values ($t = 0.529$; $p = 0.298$). Notably, these results haven't interpreted the proposed determinant as positive or negative as the evidence was inconclusive. Hedonic motivation in this study consisted of 3 survey items: HM1, HM2, and HM3.

The results of this determinant are consistent with a study by Maksim (2018), who studied the adoption of various streaming services, including Spotify.

Venkatesh et al. (2012) claim that hedonic motivation determines the level of fun or pleasure an individual has using a particular technology. In this context, several factors can impact the insignificant influence of hedonic motivation on the behavioral intentions of Spotify listeners in Azerbaijan.

One of the main reasons for the insignificant effect may be the presence of many music streaming platforms in the Azerbaijani market where users do not identify Spotify as an exclusive hedonic solution.

The second aspect could be the insufficient sample size in this research, as in the previous determinant, which did not allow for the statistical significance of this factor. Several studies in the field of the adoption of music streaming services have found a positive relation between hedonic motivation and behavioral intention (Park, 2020; Helkkula, 2016; Martins, 2013), which provides a solid basis for further investigation of the impact of this determinant in the adoption of Spotify in Azerbaijan.

Price Value

The analysis highlights that price value (PV) is an influential determinant, as evidenced by a positive beta of 0.119 ($t = 1.659$; $p = 0.049$). These empirical findings support the positive impact of price value on the behavioral intention of Spotify users in Azerbaijan. The price value in this investigation consisted of 3 survey items: PV1, PV2, and PV3.

The outcomes of this factor align with those of other researchers using the UTAUT2 adoption model in the context of music streaming services (Wagner and Hess, 2013; Helkkula, 2016; Chandra et al., 2018).

According to Venkatesh et al. (2012), the price value is positive when the benefits of using a technology are perceived to be greater than the monetary cost, and such price value positively impacts intention. In this research, several essential factors identify the positive impact of price value on the behavioral intentions of Spotify listeners.

As Suhod et al. (2022) mention, price value in the context of Spotify is related to the benefits received from Spotify's premium subscription cost. Therefore, one of the most significant factors is emphasizing the proper value proposition for premium accounts. In this regard, Spotify can highlight all the benefits of providing a clear value proposition for listeners to receive from a premium subscription. These functional advantages, for example, include increasing the quality of listening to audio content from 160 kilobits to 320 kilobits (Kreitz & Niemela, 2010) and the ability to download content for offline listening (Amalina, 2019), which can generate influential user interest in switching from freemium to premium subscription. For more tremendous success, Spotify can inform free users through various marketing channels, highlighting the relevant benefits of a premium account.

Furthermore, offering exclusive incentives and developing additional tariffs for a diverse target audience can also significantly affect the attraction of new premium Spotify subscribers in Azerbaijan.

Habit

The most influential determinant in the research was habit (H), with a significant beta coefficient equal to 0.506 (t=7.015; p=0.000). This confirms the hypothesis that habit positively affects the behavioral intention of Spotify users in Azerbaijan. The habit in this study consisted of 3 survey items: H1, H2, and H3.

The outcomes of this factor align with those of other researchers using the UTAUT2 adoption model in the context of music streaming services (Park, 2020; Chandra et al., 2018; Helkkula, 2016).

Venkatesh et al. (2012) state that habit determines the perceptual feeling that reflects the influence of previous experiences. Several considerable factors identify the positive impact of habit on the behavioral intentions of Spotify listeners.

First, playlists are the most significant factor in forming habit patterns in this context. Prey (2019) mentioned that some playlists, such as 'Discover Weekly,' 'Daily Mix,' 'Release Radar' and 'Your Summer Rewind' are generated automatically depending on user taste. Other than that, some playlists, such as 'RapCaviar' and 'Jazz Classics,' were created by the Spotify team. For this reason, focusing on updated playlists that listeners are excited to listen to daily can influence the frequency of Spotify use, ultimately positively impacting habit formation.

Secondly, the development of special reward techniques can contribute to the formation of habits. For example, a listener can accumulate points for listening to music and exchange them for a discount on the next monthly payment. Also, a special referral discount on official tickets or merchandise resources may be offered as a reward.

Behavioral Intention

Venkatesh et al. (2012) mentioned that behavioral intention represents users' desire or inclination to engage in certain behaviors associated with adopting a particular technology. Walean and Rachmawati (2018) noted that behavioral intention is used to evaluate consumers' interest in using the Spotify service.

Behavioral intention was the primary endogenous variable and the fundamental determining factor in the research model because it combines the influence of all other determinants and represents the explanatory power in this investigation. The research model explained 81.1% of the variance in behavioral intention, indicating a strong connection between this determinant and other factors toward Spotify adoption among listeners in Azerbaijan.

CHAPTER VI:

IMPLICATIONS, RECOMMENDATIONS AND CONCLUSION

6.1 Implications

This study has several significant implications that relate to both the theoretical aspects of research in the field of theories of technology acceptance and for the music streaming services industry, in particular, Spotify.

Theoretical Implication

In the first place, it is essential to note that this research contributes to the application of the theoretical construct of the Unified Theory of Technology Acceptance and Use 2 on the territory of Azerbaijan. This helps to understand the theories of technology acceptance better and analyze different socio-cultural contexts. Secondly, primary data and findings obtained using quantitative methodology can be used for comparative analysis or interpretation in future academic studies studying the adoption of Spotify users. These contributions can be implemented in different branches of science, such as sociology, innovation management, and economic psychology.

Industry Implications

For the industry, this study has several implications. The positive impact of the determinants of performance expectancy, effort expectancy, price value, and habit, as well as the negative effect of social influence on the behavioral intention of Spotify users in Azerbaijan, provides a comprehensive ground for the development of further business and marketing strategies as well as optimization of the user experience of music streaming platforms, in particular, Spotify, in the territory of Azerbaijan. Based on the findings and suggestions of this investigation, Spotify can maintain its dominant position in the highly competitive music streaming market in Azerbaijan by attracting more new customers and retaining loyal customers more effectively.

6.2 Recommendations for Future Research

This study simultaneously touches on several topics that have been researched and have a significant basis for further recommendations. The recommendations below will help researchers better understand and provide avenues for future research on analyzing Spotify and other music streaming services from a technology adoption and usage perspective, applying the UTAUT2 theoretical framework.

Cross-Cultural Context

Over the past few years, the Spotify platform has adopted a successful business expansion strategy, appearing in more and more markets. From this perspective, further research on music streaming services such as Spotify or other information technologies can be conducted in different countries and regions using the Unified Theory of Technology Acceptance and Use 2. These studies will help generalize and comprehensively understand users' adoption using UTAUT2. For example, Narotso (2022) analyzed the effects of pricing and convenience on audio streaming consumption through UTAUT2 in Nairobi, Kenya. Another example is Afonso (2019), who examined smart-speaker adoption in Portugal using the UTAUT adoption model.

For future research, it is also recommended that a comparative analysis be conducted between already explored regions or countries where similar studies have not yet been performed.

Longitudinal Studies

When considering the time horizon of this study in the methodology chapter, it is worth recalling that this study is cross-sectional. Further research can be longitudinal because it will allow for a more in-depth and detailed analysis of Spotify's user behavior and tracking changes in clients' use of Spotify over time. For example, Wang et al. (2020) investigated crowdsourcing games using the UTAUT framework with a longitudinal approach.

Qualitative Exploration

Most existing literature on studying Spotify users' adoption uses quantitative methodology. Despite this, to study this phenomenon, it is possible to use qualitative and, if necessary, mixed methods, including both qualitative and quantitative. When choosing a qualitative methodology, interviews or focus groups can be used to collect primary data. For instance, Gharaibeh et al. (2018) investigated the adoption of mobile banking services using a qualitative approach. These studies will help provide more holistic results for testing this or similar theoretical technology acceptance models.

Theory Development

Although most studies examining the adoption of Spotify users have focused exclusively on investigating the effects of performance expectancy (PE), effort expectancy (EE), social influence (SI), favorable conditions (FC), hedonic motivation (HM), price value (PV) and habits (H) to behavioral intention (BI), future studies can use additional moderators from the original UTAUT2 model, such as age, gender, and experience, to provide more in-depth analysis in the field of Spotify adoption and usage studies.

In addition, future research could synthesize determinants from the current theoretical model and other technology acceptance models. For example, Suhod et al. (2022) investigated Spotify Premium among university students using the "Ubiquity" extension for UTAUT2. Modifying the standard theoretical model can help further explore Spotify users' behavior and usage, specifically in a given context.

Specific Customer Segments

Although most studies of music streaming services using technology acceptance theories use geographic settings such as country or specific region as respondents, future research could focus on more specific consumer segments. In this case, there can be several successful examples for further implementation. For example, it may only be the comparative adult generation of users whose empirical results will differ from the more technologically advanced younger generation. These can also be users of only the free or paid version of the Spotify platform. For instance, Becagli et al. (2020) investigated empirical evidence from Spotify Premium users, and Amalina (2019) researched differences between free and premium users. The study may also use gender, income level, behavioral habits, etc., to define a specific customer segment.

6.3 Conclusion

This investigation aimed to comprehensively analyze the adoption of the music streaming service Spotify in Azerbaijan using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework. This study researched the influence of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habits on the behavioral intentions of Spotify users in Azerbaijan.

The research found that performance expectancy, effort expectancy, price value, and habit positively influenced the behavioral intention of Spotify users in Azerbaijan. Furthermore, the unexpected result of this research was the negative influence of social influence on behavioral intention. The proposed factors explained 81.1% of the variance of behavioral intention to use Spotify in Azerbaijan. Other factors, such as facilitating conditions and hedonic motivation, were statistically insignificant. Therefore, the study also recommended investigating these factors for future research.

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APPENDIX A

PARTICIPANT CONSENT FORM

Tədqiqatın Başlığı: Texnologiyanın Qəbul və İstifadəsinin Vahid Nəzəriyyəsi 2 istifadə edərək Azərbaycanda Spotify-ın təhlili

Tədqiqatçı: Sabir Zeynalov

Giriş: Siz SSBM Cenevrə Universitetinin tələbəsi Sabir Zeynalov tərəfindən Biznesin idarə edilməsi üzrə doktorluq proqramı çərçivəsində aparılan tədqiqat işində iştirak etməyə dəvət olunursunuz. Bu tədqiqatın məqsədi Texnologiyanın Qəbul və İstifadəsinin Vahid Nəzəriyyəsi 2 (UTAUT2) çərçivəsindən istifadə edərək Azərbaycanda musiqi striminq xidməti olan Spotify-ın qəbulu və istifadəsini hərtərəfli təhlil etməkdir.

Tədris Prosedurları: İştirak etməyə razılaşsanız, sizdən sorğu anketinin doldurulması xahiş olunacaq. Anketə demoqrafik məlumatlarınız, Spotify tətbiqi ilə təcrübəniz, onun istifadəyə yararlılığı və faydalılığı ilə bağlı suallar daxil olacaq. Sorğunun təxminən 15 dəqiqə çəkəcəyi gözlənilir.

Risk və Faydalar: Bu tədqiqatda iştirak risksizdir və siz birbaşa fayda əldə etməyəcəksiniz. Lakin, sizin iştirakınız Spotify tətbiqinin Azərbaycanda istifadəsini başa düşməyə kömək edəcək və bu sahədə gələcək tədqiqatlar üçün faydalı ola biləcək.

Məxfilik: Cavablarınız məxfi qalacaq. Məlumatlarınız cavablarınız ilə əlaqələndirilməyəcək; bütün məlumatlar məxfi saxlanılacaq. Məlumatlara giriş icazəsi yalnız baş tədqiqatçıya məxsus olacaq.

Könüllü İştirak: Bu tədqiqatda iştirak könüllüdür. Səbəb göstərmədən tədqiqatdan imtina etmək hüququnuz var.

Razılıq: Aşağıdakı xananı işarələməklə yuxarıdakı məlumatları oxuduğunuzu, suallarınıza qənaətbəxş cavab verildiyini və könüllü olaraq bu tədqiqatda iştirak etməyə razılaşdığınızı təsdiq edirsiniz**.**

☐ Tədqiqatda iştirak etməyə razıyam.

APPENDIX B

QUESTIONNAIRE USED IN THIS RESEARCH

1) Cinsinizi seçin

   Kişi

   Qadın

2) Yaşınızı seçin

   <18

   18-25

   26-40

   41-55

   >56

3) Ən yüksək təhsil səviyyəniz

   Orta məktəb

   Kollec

   Bakalavr dərəcəsi

   Maqistr dərəcəsi

   Doktorluq dərəcəsi

Items	Survey Questions
PE1	Spotify-ı gündəlik həyatımda faydalı hesab edirəm.
PE2	Spotify-dan istifadə işlərimi daha tez yerinə yetirməyə kömək edir.
PE3	Spotify-dan istifadə məhsuldarlığımı artırır.
EE1	Spotify-dan istifadə etməyi öyrənmək mənim üçün asandır.
EE2	Spotify ilə qarşılıqlı əlaqəm aydın və başa düşüləndir.
EE3	Spotify-dan istifadəni asan hesab edirəm.
EE4	Spotify-dan istifadə etməkdə bacarıqlı olmaq mənim üçün asandır.
SI1	Mənim üçün önəmli olan insanlar Spotify-dan istifadə etməli olduğumu düşünürlər.
SI2	Davranışıma təsiri olan insanlar Spotify-dan istifadə etməli olduğumu düşünürlər.
SI3	Fikirlərinə dəyər verdiyim insanlar Spotify-dan istifadə etməyimi məsləhət görürlər.
FC1	Spotify-dan istifadə etmək üçün lazımi resurslarım var.
FC2	Spotify-dan istifadə etmək üçün lazımi biliyə malikəm.
FC3	Spotify istifadə etdiyim digər texnologiyalar ilə uyğun gəlir.
FC4	Spotify-dan istifadə etməkdə çətinlik çəksəm, başqalarından kömək istəyə bilərəm.
HM1	Spotify-dan istifadə əyləncəlidir.

HM2	Spotify-dan istifadə etmək xoşdur.
HM3	Spotify-dan istifadə çox əyləncəlidir.
PV1	Spotify münasib qiymətədir.
PV2	Spotify qiymət və keyfiyyətin sərfəli nisbətidir.
PV3	Cari qiymətə görə, Spotify yaxşı bir dəyər təmin edir.
H1	Spotify-dan istifadə mənim üçün vərdişə çevrilib.
H2	Spotify-dan istifadə etməkdən asılıyam.
H3	Spotify-dan istifadə etməliyəm.
BI1	Gələcəkdə Spotify-dan istifadəni davam etdirmək niyyətindəyəm.
BI2	Gündəlik həyatımda həmişə Spotify-dan istifadə etməyə çalışacağam.
BI3	Spotify-dan tez-tez istifadəni davam etdirməyi düşünürəm.

Likert Scale	**Answers**
1	Qəti razı deyiləm
2	Razı deyiləm
3	Neytral
4	Razıyam
5	Tamamilə razıyam

APPENDIX C

MUSIC STREAMING STATISTICS IN AZERBAIJAN

The table below shows **the number of active paying customers** (or accounts) in Azerbaijan, according to Statista.com.

Year	2017	2018	2019	2020	2021	2022	2023
Total	0,4	0,4	0,4	0,5	0,6	0,5	0,6

** in millions for each year.*

The table below shows **the revenue development** in Azerbaijan, according to Statista.com.

Year	2017	2018	2019	2020	2021	2022	2023
Total	2,74	3,14	3,70	4,95	5,76	5,40	5,77

**in million USD for each year.*

APPENDIX D

THE SMARTPLS RESULTS OF THE RESEARCH MODEL