Lisbon School of Economics & Management
Universidade de Lisboa

MASTER

DATA ANALYTICS FOR BUSINESS

MASTER´S FINAL WORK

DISSERTATION

TIKTOK'S INFLUENCE IN MUSIC CONSUMPTION

LEONOR GONÇALVES AMANTE DE MATOS TRIGO

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SUPERVISION:
PROF. CARLOS J. COSTA

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Glossary

AVE – Average Variance Extracted.

CR – Creator Influence.

EE – Effort Expectancy.

FC – Facilitating Conditions.

FYP – For You Page.

GAM – Gamification.

HM – Hedonic Motivation.

INT – Streaming Intention.

MFW – Master's Final Work.

PDV – Perceived Discovery Value.

PI – Peer Influence.

PLS – Partial Least Squares.

SEM – Structural Equation Modeling.

TEI – TikTok Engagement Intensity.

U – Use.

UTAUT – Unified Theory of Acceptance and Use of Technology.

VIF – Variance Inflation Factor.

ABSTRACT

In the 21st century, social media has become a channel for people to communicate with others about their interests. The widespread use of these platforms, combined with the growing power of AI algorithms and machine learning, makes them a powerful tool for businesses across industries. Within the music industry, social media platforms play a significant role by enabling the promotion of songs and live events, facilitating music discovery, expanding audience reach, and allowing artists to engage directly and authentically with listeners.

This study aims to understand which factors related to TikTok can lead to people listening to songs and saving them on playlists in music-streaming platforms. To address this research question, a model grounded in the UTAUT framework was developed and extended with some new constructs specific to the research subject. An online survey was conducted to collect data regarding TikTok and music-streaming platforms use, which was then analyzed with Structural Equation Modeling.

The model consisted of ten hypotheses, which were all empirically supported. Results showed that the use of streaming platforms can be predicted by facilitating conditions and intention to stream. Intention can be explained by hedonic motivation, perceived discovery value, effort expectancy, and peer influence. Gamification and creator influence make people perceive music discovery on TikTok as more valuable. Creators can also make using TikTok to discover music less difficult, lowering effort expectancy. Lastly, it is possible to state that facilitating conditions can result in higher enjoyment of TikTok use, increasing hedonic motivation.

KEYWORDS: TikTok; Social Media; Music.

JEL CODES: D12; L82; L86; Z11.

Resumo

No século 21, as redes sociais tornaram-se um canal através do qual as pessoas comunicam com outras sobre os seus interesses. O uso generalizado destas plataformas, combinado com o poder crescente dos algoritmos de IA e aprendizagem automática, torna-as uma ferramenta poderosa para empresas em diferentes indústrias. Na indústria da música, as plataformas de redes sociais têm um papel significante ao possibilitarem a promoção de músicas e eventos ao vivo, facilitarem a descoberta de música, expandirem o alcance do público, e permitirem aos artistas interagirem diretamente e autenticamente com os ouvintes.

Este estudo tem como objetivo perceber quais os fatores relacionados com o TikTok que levam as pessoas a ouvir músicas e guardarem-nas em playlists de plataformas de *streaming* de música. Para abordar esta questão de investigação, um modelo baseado na estrutura UTAUT foi desenvolvido e alargado com alguns novos construtos específicos do tema da investigação. Um inquérito online foi realizado para recolher informação relativa ao TikTok e ao uso das plataformas de *streaming* de música, que foi depois analisada através do Modelo de Equações Estruturais.

O modelo consiste em 10 hipóteses, que foram todas apoiadas empiricamente. Os resultados mostram que o uso das plataformas de *streaming* pode ser determinado por condições facilitadoras e intenção de *streaming*. A intenção pode ser explicada através da motivação hedónica, perceção do valor da descoberta, expectativa de esforço e influência dos pares. A gamificação e a influência dos criadores de conteúdo fazem com que as pessoas percecionem a descoberta de música no TikTok como mais valiosa. Os criadores também fazem o uso do TikTok para descobrir música menos difícil, reduzindo a expectativa de esforço. Em último lugar, é possível afirmar que as condições facilitadoras podem resultar numa maior satisfação no uso do TikTok, aumentando a motivação hedónica.

Palavras-chave: TikTok; Redes Sociais; Música.

Códigos JEL: D12; L82; L86; Z11.

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1. INTRODUCTION

1.1. Context and Motivation

Music has been a fundamental part of human culture for centuries, evolving along with technology and society (Cross, 2001). The ways that people listen to music have changed over the past 20 years, from physical formats like vinyl records and CDs to digital formats like MP3s. However, these earlier technologies limited the users to listen to what was contained in their own collection of albums or singles.

Recently, music-streaming services have provided a major shift in the experience of listening to music by providing consumers with vast collections of music that contain millions of songs at a relatively affordable price. In addition, advancements in artificial intelligence (AI) and machine learning (ML) have enhanced the abilities of these platforms to personalize the listener's experience. Through the use of algorithms that provide personalized music recommendations to each listener, streaming platforms have developed customized playlists based upon each individual's history and preferences (Sguerra et al., 2022). Therefore, the global utilization of music-streaming services has altered the way individuals engage with music as well as the process of finding new artists and music utilizing algorithm-based recommendations over traditional media outlets (Freeman et al., 2022). This way, music-streaming platforms reduce both the financial cost of music consumption and the time listeners spend discovering new content.

These advances in algorithms and machine learning also apply to social media, which plays a central role in shaping artists' careers, as it directly influences how visible artists are, how their music reaches potential audiences, and how commercial success is achieved. A review of the Billboard Hot 100 Chart in 2024 clearly illustrates this point since many of the top songs were first introduced to large audiences via TikTok before achieving high positions on the Billboard Hot 100 Chart (TikTok & Luminate, 2025). Social media platforms have also become an important resource for artists to obtain fan feedback to help guide future releases and develop a stronger relationship with their fans by posting behind-the-scenes content and personal updates. Consequently, social media and music-streaming platforms are closely connected and affect both consumer behavior and other stakeholders in the music industry.

1.2. Research Question and Objectives

According to the International Federation of the Phonographic Industry (IFPI, 2025), in 2024, 69% of global recorded-music industry revenues were obtained from streaming. Concurrently, TikTok has approximately 1.59 billion active users worldwide, and about 85% of its content includes music (DataReportal, 2025; Digital Music News, 2024). This overlap between music and social media presents a compelling area of investigation. Understanding how users engage with music across both platforms can offer deeper insights into music discovery and music consumption behaviors. The research question guiding this study is therefore: What factors related to TikTok influence music-streaming habits? The study also aims to understand other aspects, such as the difference in the impact of peers and creators on TikTok, and the possibility of introducing gamification features related to music on TikTok.

To address this question, a conceptual model based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) is proposed. The study follows a quantitative research approach, using a structured questionnaire administered to users of both TikTok and music-streaming services. The survey collects data on social-media engagement, music-streaming behavior, and relevant demographic variables. The collected data will be analyzed using Structural Equation Modeling (SEM) and Smart PLS to evaluate the validity of the proposed model and test the associated hypotheses.

1.3. Report Structure

The report begins with a literature review, focusing on the evolution of the music industry, the rise of music-streaming platforms, and the role of social-media platforms, particularly TikTok, in shaping music discovery and consumption behaviors. Afterwards, the proposed conceptual model will be explained, and the corresponding research hypotheses will be described. Subsequently, the research methodology will be clarified, including the research design, data-collection procedures, questionnaire structure, and analytical techniques employed. Results from the questionnaire will then be analyzed, using Structural Equation Modeling (SEM) to test the proposed model and evaluate the validity of the hypotheses. The findings will then be interpreted and discussed in relation to existing literature. Key findings will be summarized in the final chapter. In this chapter, implications of the study, limitations, and future research will also be discussed.

2. Literature Review

In this chapter, the relevant aspects of the study are presented and discussed through a review of existing literature. The first section describes the development of the music industry, culminating in an analysis of the most prominent music-streaming services and their critical role in shaping contemporary patterns of music consumption. The subsequent section explores the evolution of TikTok, from its creation to the widespread influence it exerts on global audiences in 2025.

2.1. Music Industry

For a significant part of human history, music predominantly existed as a live, shared experience. Its dissemination depended on oral traditions, regional instruments, and social gatherings (Cross, 2001). The creation of musical notation during the Middle Ages enabled music to be documented and distributed across geographical boundaries, establishing a foundation for a more structured music economy (Taruskin, 2005).

The creation of sound recording in the late 19th century transformed the music industry. Thomas Edison's phonograph (1877) and Emile Berliner's gramophone (1887) enabled music to be recorded and played back, changing it from a fleeting art form into a reproducible product. In 1889, the first music label, Columbia Records, was created. The later emergence of the recording industry in the early 20th century allowed artists to connect with audiences outside concert venues, laying the groundwork for a worldwide market (Gronow & Saunio, 1998).

The radio revolutionized the industry by delivering music straight into homes and fostering the emergence of mass media celebrities. The postwar period (1940s–1960s) witnessed the dominance of record labels that managed production, marketing, and distribution, influencing the careers of artists and the preferences of listeners (Wayte, 2023).

The late 20th century brought about a digital shift that significantly altered the conventional music industry. The compact disc (CD), launched in the early 1980s, represented the industry's initial significant venture into digital audio playback. Although CDs initially enhanced record sales, the rise of MP3 compression and peer-to-peer file sharing sites like Napster in the late 1990s weakened traditional distribution models (Wikström, 2013).

With digital files and music downloads available, digital piracy spread rapidly, which meant record labels no longer had control over music distribution and exposed weaknesses in existing revenue models. In response, legitimate digital download stores, such as Apple's iTunes, launched in 2003, providing a legal alternative, enabling users to purchase individual tracks rather than full albums. This shift toward consumer choice marked the beginning of a new, user-centered era in music consumption (Wayte, 2023).

The 2010s witnessed another significant transition with the widespread adoption of music-streaming platforms, such as Spotify, Apple Music, and YouTube Music. These services transformed how people access and experience music by offering vast catalogs through subscription or ad-supported models, unlike earlier eras, where ownership of music (via records, CDs, or downloads) was crucial, streaming redefined value around accessibility and personalization (Morris & Powers, 2015).

Streaming services use algorithmic recommendation systems that create playlists and song suggestions based on user preferences. This has reshaped the process of music discovery, reducing reliance on traditional media outlets and radio programming (Freeman et al., 2022). To summarize, streaming has lowered both the financial barriers to music consumption and the time required to discover new content.

The most popular music-streaming platform is Spotify, created in 2008 in Stockholm, Sweden. This platform has 713 million users, 281 million of whom are subscribers in more than 180 countries (Spotify Technology S.A., 2025). This represents 35 percent of the global music streaming market share (Azfar, 2025). Its library contains more than 100 million songs, 6.5 million podcast titles, and 350 thousand audiobooks (Spotify Technology S.A., 2026).

In 2014, Spotify acquired the music analytics firm The Echo Nest, leading to the incorporation of more complex data techniques. Spotify collects data about songs, users, and their interactions with the app. Specifically, playback history (songs that the user listened to frequently, or on the contrary, skipped often), songs added to playlists, song popularity (in general and among users with similar taste), friends' listening patterns (to understand what songs are popular in the user's social circle) are all considered (Anderson et al., 2020). In addition, data from external sources is also considered, such as device usage, to understand the users' profiles, and location data, which is used to recommend popular songs in the area or inform them when artists have a show near them (Pragmatic Institute, 2025).

This data is then used to create insights through techniques that can be grouped in two categories: collaborative filtering and content-based filtering.

Collaborative filtering examines the relationships between users and tracks by identifying patterns in listening behavior (Freeman et al., 2022). Different analytical approaches are used to study these patterns. In user-based filtering, recommendations are generated by selecting songs that users with similar listening profiles have enjoyed, while item-based filtering recommends songs similar to those the user likes (Anderson et al., 2020). Content-based filtering focuses on the characteristics of the track itself. This method uses both metadata attributes (title, artist name, genre, language, and duration) and audio attributes (danceability, energy, valence, tempo, and acousticness) to suggest musically similar content (Stanisljevic, 2020). These methods are used in a combined way, creating a hybrid model that enables more accurate and personalized music recommendations by considering both user behavior and the musical characteristics of tracks (Freeman et al., 2022).

These recommendations are delivered to users in different ways. For instance, Discover Weekly is a playlist that is updated every Monday, where listening data is used to provide new recommendations. Release Radar is another tool that makes users aware of new releases by artists they listen to. Personalized playlists combining genres, such as rock, pop, or country, with listening history are also available. These tools are seen by users as important and their impact and usefulness regarding music discovery is also recognized (Stanisljevic, 2020).

Besides song recommendations, data is also leveraged in other ways to enhance the user experience. One example is Spotify Wrapped, a personalized report for each user. This information is provided to listeners and to artists. For listeners, it contains their most listened to artists and songs, the time spent on the app, and even messages from artists to top fans (Spotify Newsroom, 2025). For artists, it includes figures such as the number of streams and listeners, and geographic distribution of listeners, which is useful information for the artist and record labels. The data derived from these platforms also provides valuable insights for artists and labels that were not available before the digital era, such as the number of times a song is streamed, shared, or searched for (Spotify for Artists, 2023).

This personalization of music consumption explains the success of these tools and why, since 2017, streaming has been the main source of revenue of the global recorded music industry. Indeed, its relevance has increased over the past decade. In 2017, it accounted for 40% of the industry's earnings, followed by physical copies representing almost 30% of the revenue. In 2024, its share had increased to 69% of global recorded music revenue, while physical copies remained in second place, representing only 16% of these earnings. Streaming revenue can further be divided into ad-supported streaming (17.7%) and subscription streaming (51.2%). When compared to 2023, these numbers reflect a 9.5% growth in subscription streaming revenues and a 1.2% growth in ad-supported streaming, resulting in a combined 7.3% increase in global streaming revenue. These earnings are explained by the 752 million users of subscription accounts. In an inverse trajectory, physical revenues declined 3.1% (IFPI, 2025).

Studies have been developed in order to understand the factors driving the adoption of paid music-streaming services. A study from 2021 revealed that performance expectancy, effort expectancy, hedonic motivation, price value, habit, perceived freemium-premium fit, and attitude towards piracy are all strong predictors of the use of these tools (Barata & Coelho, 2021). Facilitating conditions and social influence are two of the constructs that seem less important, perhaps due to the widespread use of technology. Additionally, personalization and intention to buy help to explain the recommendation of these services. Another study showed that people with higher consumption diversity are more likely to convert to regular Spotify users and to pay for a Spotify subscription. The same study also demonstrated that algorithmic-driven listening is less diverse than organic listening. Therefore, in order to keep users satisfied and engaging with the platform, it is important to ensure that algorithms do not create a filter bubble and allow listeners to discover different songs, genres and artists (Anderson et al., 2020).

Even though streaming is the biggest source of income for this industry, this is not reflected in artists' earnings. Indeed, musicians have shared concerns regarding this business model. Platforms like Spotify or Apple Music use a model called Pro Rata (Sisario, 2021). Applied to streaming, this model means that the subscription fees of all users are aggregated and then distributed proportionally according to the number of streams of each artist (Lei, 2023). In practice, this means that if a certain artist has 5 percent of all the streams, they get 5 percent of the total subscription fees, even of the subscribers who never listened to their songs. In addition, music is usually partly or totally owned by a record label that receives a share of these fees, sometimes a percentage as high as 85 percent (Schwartz & Clark, 2020). Therefore, the money musicians make from streaming is not reliable as their main source of income.

In parallel to the mainstream music industry, where songs are produced and marketed by labels, there has been a rise in the number of independent artists who produce and distribute their music on their own through the use of third-party services. The success of these artists is enabled by social media, which gives them access to new audiences from anywhere in the world. By not working with a record label and a team, they control what they post and get the profits that would, in the traditional model, be split amongst intermediaries (Wayte, 2023).

2.2. Social Media

Social media platforms can be described as "a group of interactive Web 2.0 Internet-based applications that allow users to create and exchange user-generated content via virtual communities" (Gong & Yang, 2020).

One of the first widely successful examples of these platforms is Facebook, launched in 2004. Mark Zuckerberg, a student at Harvard University, created it. Initially, the site was used by students at that university. It gradually became available to students of other universities in the US, high schools, and by 2006, it was available to anyone with an email address (Phillips, 2007).

In 2005, YouTube was created. The platform, which is based on videos, has played a central role in launching the careers of several contemporary artists, including Justin Bieber, Shawn Mendes, and 5 Seconds of Summer (5SOS). These artists share a similar trajectory: they began by posting cover versions of popular songs on the platform, gradually attracting audiences before being discovered by influential figures within the music industry (Brandle, 2014; Official Charts, 2014). In the case of 5 Seconds of Summer, their visibility increased substantially in 2012 when Louis Tomlinson, a member of One Direction, one of the world's most popular bands at that time, shared a link to one of their YouTube videos on Twitter. This exposure introduced the group to One Direction's extensive fanbase and eventually led to 5SOS joining two of the band's world tours as an opening act, which significantly accelerated their rise to international fame. Since then, 5 Seconds of Summer have released multiple studio albums and performed globally in sold-out venues (Dembo, 2022).

One of the most recent social media platforms to become popular is TikTok, a short-form video platform developed by the Chinese technology company ByteDance and launched internationally in 2017. It evolved from Douyin, which ByteDance introduced in China in 2016, enabling users to create brief videos enhanced with music, filters, and editing tools (Shutsko, 2020). TikTok quickly gained traction outside China due to its intuitive interface, integration with popular music, and emphasis on creative, rapidly consumable content. A major catalyst for its global expansion was ByteDance's acquisition of Musical.ly in 2017, a U.S.-based lip-syncing platform with a substantial teenage user base. The merger of Musical.ly into TikTok in 2018 unified their user communities and consolidated TikTok's presence across North America and Europe, reaching hundreds of millions of users (Montag, Yang, & Elhai, 2021).

TikTok's development stands in contrast to earlier social media platforms. Instagram, launched in 2010, was primarily designed for photographic sharing and visual curation, while YouTube positioned itself as a repository for long-form video content, including vlogs, tutorials, and podcasts. TikTok distinguished itself by popularizing short-form, music-driven videos, which encouraged a new mode of creative expression centered on dance, comedy, and participatory trends. Its unprecedented growth prompted competing platforms to adopt similar features: Instagram introduced Reels and YouTube launched Shorts, leading many creators to post identical or adapted videos across multiple platforms, and spreading TikTok's short-video format throughout the social media ecosystem (Abidin, 2020).

A defining feature of TikTok is its For You Page (FYP), powered by a hybrid content- and behavior-based machine-learning recommendation system. Unlike traditional feeds that primarily display posts from followed accounts, the FYP shows content from any creator if the algorithm predicts user interest. TikTok's ranking system incorporates user interactions (such as likes, shares, and comments), video information (e.g., captions, sounds, and hashtags), and device settings, with watch time, re-watches, and completion rate being among the strongest predictors of recommendation. The algorithm also interprets micro-behaviors such as pausing, rewatching, and hovering, continuously refining its inference of user preferences (Boeker & Urman, 2022).

The virality of a TikTok video featuring music is affected by the characteristics of the song, as well as the users' interaction with the content. Specifically, defining virality as the number of likes, a study has shown that the number of shares is its most relevant predictor, elucidating the importance of social interactions on the virality of a video using music and, consequently, of the music used in it (Rahardjo et al., 2024).

It is important to acknowledge the criticisms that TikTok has faced. Scholars argue that the platform's algorithmic recommendation system can contribute to the emergence of "filter bubbles" or "echo chambers," where users are predominantly exposed to content that aligns with their existing preferences, opinions, and beliefs. This dynamic can reinforce cognitive and cultural biases, limiting exposure to diverse perspectives and potentially shaping user behavior in subtle but significant ways (Bhandari & Bimo, 2022). The concerns regarding the use of TikTok's recommendation engine to personalize users' experiences are linked to other issues, such as data governance and users' rights to privacy. Fears over the collection, handling, and potential transfer of user data contributed to legislative efforts in the United States to restrict or temporarily ban the platform (U.S. Congress, 2024). These concerns are closely linked to the fact that TikTok's parent company, ByteDance, is headquartered in China, where data protection laws differ substantially from those in Europe and North America, raising questions about the security and sovereignty of user information (Rubbert, 2025).

Nonetheless, TikTok is a tool that can be used by many people, including music artists, to enable their success by increasing exposure and reaching people from all around the world. On platforms like Instagram or Facebook, the only way one could learn about upcoming concerts or the release of a musician's new song would be to follow their account. In contrast, TikTok is a discovery mechanism for musicians and record labels, due to the role of the For You Page (FYP) (Whateley, 2024).

Musicians can use TikTok to build engagement by posting behind the scenes videos, making of songs, and personal, informal videos. This strengthens the bond between the audience and the artist, making people more likely to engage and become fans. Because platforms like TikTok give artists the ability to market themselves directly and grow an audience without a label, they can enter contract negotiations with more leverage. Labels often offer better terms, such as higher royalty rates or shorter contract lengths, to artists who already bring a proven fanbase and established online visibility.

TikTok's growing relevance in the music industry has been recognized by major record labels, which use the platform to promote new releases and identify emerging artists. In fact, the platform has signed licensing deals with the three most important record labels: Sony Music, Warner, and Universal. Michael Nash, Executive Vice President and Chief Digital Officer at Universal Music Group, affirmed that social media remains a golden opportunity for creative growth (IFPI 2023). In February of 2024, Universal Music Group decided to remove songs by their artists from TikTok because of a disagreement in adequate compensation for the music used on the platform. Research on the USA and Germany markets' shows that this resulted in a 2-3% increase in streams on music-streaming platforms for affected songs, possibly due to substitution effects. Interestingly, older songs and songs with less promotional support elsewhere saw a decrease in streaming consumption, suggesting that TikTok helps consumers discover or rediscover content (Winkler et al., 2024). This lasted a few months, and in May, an agreement was reached, and the label returned to TikTok. The platform maintains a dedicated music team led by former Warner Music executive Ole Obermann, responsible for artist relations, licensing, and music-specific initiatives.

TikTok is aware of its effect, which is why in 2023 it partnered with Luminate to release a yearly Music Impact Report. Luminate is the platform used as a standard measurement to track sales, streams, downloads, and airplay of music. Billboard charts, one of the most recognized in the music industry, are built using this data. This report synthesizes information from music charts, TikTok platform analytics, and survey findings from TikTok users in the United States. The most recent report, relative to 2024 and released in February of 2025, contains important insights. The fact that 84% of songs that entered the Billboard Global 200 in 2024 went viral on TikTok first illustrates its relevance regarding music discovery. Concurrently, TikTok is also a means for older music to be rediscovered. A song is categorized as a "catalog song" when it has been released for at least 18 months. In 2024, over 50 different catalog songs entered the Billboard Global 200 after going viral on TikTok. In 2024, TikTok released a new feature, "Add to Music App", which allows users to add songs used in TikTok videos directly to a music app such as Spotify, Apple Music, and Soundcloud. Since then, TikTok has generated 1 billion song saves on these platforms (TikTok & Luminate, 2025).

Interesting studies have been developed to understand TikTok's relation to the music industry. A study from 2023 about five independent artists showed that posting relatable and informative content on TikTok, with which fans can easily engage, can increase streaming success. The artists with the highest amount of fan engagement on TikTok also had a higher conversion rate to Spotify (Mallard, 2023). Another study, regarding more famous songs and artists, compared metrics of some of the top songs of the Billboard 2021 Year-End Hot 100 chart with their respective TikTok's hashtag views and number of times the sound was used. These songs, with millions of Spotify listeners and streams, also proved to be extremely popular on TikTok, being used in millions of videos and with hashtags that were also viewed millions of times (Jorgenson, 2022). This elucidates the relationship between an artist's success and their popularity on TikTok. Research based on data from TokBoard (a website aggregating popularity data from TikTok) and Google Trends also demonstrates that TikTok is linked to the re-popularization of songs, showing that it is not only useful to artists with recent releases (Matos et al., 2024). While proving to be useful for the industry, studies also report that the rise of social media platforms like TikTok can have an impact on artists' health and wellbeing. The constant pressure to post on social media may result in less time to write or record music, and also increases comparison and competition (Wares et al., 2023; Zhang, 2024).

Considering the wide spread of TikTok use and the fact that streaming is the main way of listening to music nowadays, it is relevant to understand if there is a connection between the two, and if the use of TikTok influences the streaming behaviors of users.

2.3. Techonology Adoption

Several models and theories have been developed in order to understand consumer acceptance and adoption of technologies. In this chapter, the theories and models on which the conceptual model is based, such as the Theory of Reasoned Action, the Theory of Planned Behavior, the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, the Theory of Uses and Gratifications and the Self-Determination Theory will be addressed.

The Theory of Reasoned Action, developed by Fishbein and Ajzen in 1975, proposes that behavior is determined by behavioral intention, which is shaped by attitudes regarding that behavior and subjective norms of the users' community. Attitude is defined as an individual's evaluation of an object, and it is formed based on beliefs about the object. The subjective norms are the individual's perception of the community's attitude to a certain object of behavior. Therefore, this theory explains the intention to perform a behavior through the individual's evaluation of that behavior and the community's perception of it (Lai, 2017).

In 1991, Ajzen conceived the Theory of Planned Behavior. This theory maintains attitude and subjective norms as determinants of behavior intention, and incorporates another factor, the perceived behavioral control. This factor refers to the individual's perception of limitations that can affect their behavior (Lai, 2017).

The Theory of Planned Behavior was decomposed in 1995 by Taylor and Todd. The three main components (attitude, subjective norms and perceived behavioral control) are divided into subcomponents, creating the Decomposed Theory of Planned Behavior. Attitude is decomposed into relative advantage, complexity, and compatibility. Subjective norms correspond to one subcomponent, normative influences. Lastly, perceived behavioral control is composed of efficacy and facilitating conditions (Taylor & Todd, 1995; Lai, 2017).

The Technology Acceptance Model (TAM) was first proposed by Fred Davis in 1986, to model users' adoption of information systems and technologies (Lai, 2017). In 1996, the final version of the model was developed by Davis and Venkatesh. This model focuses on perceived usefulness and perceived ease of use as main predictors of the intention to use a technology, and consequently its use. Perceived usefulness measures the degree to which an individual understands that using the system will improve their work performance, while perceived ease of use refers to the perception of the amount of effort required to use the system. The model also considers external variables such as computer self-efficacy, objective usability, and direct experience, affecting both perceived usefulness and perceived ease of use (Davis et al., 1989; Venkatesh & Davis, 1996). Subsequently, TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008) were formulated, with the goal of further specifying the variables that explain perceived ease of use and perceived usefulness of a system.

In 2003, the Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. This theory considers performance expectancy, effort expectancy and social influence as the main predictors of users' behavioral intention, which in turn determines actual behavior. Performance expectancy measures the degree to which an individual believes that the use of a system will increase work performance. Effort expectancy relates to the degree of ease associated with consumers' use of technology. Social influence measures the consumers' perception that people around them believe they should use a particular technology. Lastly, facilitating conditions, which are considered to directly affect the behavioral use, refer to the perception of availability of resources and support to perform a behavior. The model also introduces moderating variables such as gender, age, experience, and voluntariness (Venkatesh et al., 2003). UTAUT2, created in 2012, incorporates hedonic motivation, price value and habit into the previous UTAUT model, as direct predictors of behavioral intention. Hedonic motivation refers to the fun or pleasure derived from using a technology. Price value is considered in order to measure the impact of a technology's price on its use. Finally, habit is defined as the degree to which people tend to perform behaviors automatically based on what they have already learned (Venkatesh et al., 2012).

The Theory of Uses and Gratifications, developed by Katz, Blumler, and Gurevitch in 1973, explains technology use as a result of individuals' active choice to satisfy specific needs. The theory assumes that users are goal-oriented and select technologies based on the gratifications they expect to obtain, such as information seeking, entertainment, social interaction, or enjoyment. In the context of technology adoption, the theory suggests that usage behavior is driven by the perceived benefits and satisfaction derived from technology use rather than by technological characteristics alone (Katz et al., 1973).

The Self-Determination Theory, proposed by Deci and Ryan in 1985, explains behavior through different types of motivation, particularly intrinsic and extrinsic motivation. The theory posits that motivation is influenced by the fulfillment of three basic psychological needs: autonomy, competence, and relatedness. In technology adoption studies, the theory has been used to explain how technologies that support these needs enhance users' motivation, positively influencing behavioral intention, engagement, and continued use (Deci & Ryan, 1985)

3. PROPOSED MODEL

The construction of the model used in this study was grounded in a comprehensive analysis of existing literature on technology adoption and digital media consumption. Based on this review, several core dimensions were integrated into the model, based on the models and theories presented in the previous chapter, drawing primarily from the UTAUT and UTAUT2 frameworks. The Unified Theory of Acceptance and Use of Technology provides an appropriate foundation for this research, as it studies factors such as usefulness, ease of use, enjoyment, social influence, and facilitating conditions which shape behavioral intention and actual use of technologies. Specifically, effort expectancy, facilitating conditions, hedonic motivation, and use were incorporated, as well as performance expectancy, reframed as perceived discovery value, and behavior intention, reframed as streaming intention, given their established relevance in explaining behavior intention and technology use. The Theory of Uses and Gratifications also justifies the role of hedonic motivation in technology acceptance and its incorporation into the model.

Social influence, a relevant construct of the UTAUT framework, was divided into peer influence and creator influence, since it is important to differentiate the effects that creators/ influencers and peers might have when it comes to TikTok use and music streaming.

Gamification is incorporated as a complementary construct, grounded in Self Determination Theory and prior gamification research, acknowledging the role of playful, reward-based, and comparative features in enhancing perceived value in non-game digital environments.. Given that it is already present in music-streaming platforms, for instance, in Spotify with Spotify Wrapped, it is interesting to explore if it can affect user's behavior, as it has for other non-game contexts.

Table 1 contains the definitions of every variable used to build the model, as well as their corresponding authors.

TABLE I – Proposed Model Dimensions

Construct	Definition	Author
Perceived Discovery Value (PDV)	Belief that using the system improves performance.	Venkatesh et al., (2003)

Effort Expectancy (EE)	The degree of ease associated with consumers' use of technology.	Venkatesh et al.(2003)
Facilitating Conditions (FC)	Consumers' perceptions of the resources and support available to perform a behavior.	Venkatesh et al. (2003)
Creator Influence (CR)	The extent to which consumers perceive that creators/influencers believe they should use a particular technology.	Venkatesh et al. (2003)
Peer Influence (PI)	The extent to which consumers perceive that friends/family believe they should use a particular technology.	Venkatesh et al. (2003)
Hedonic Motivation (HM)	The fun or pleasure derived from using a technology.	Venkatesh et al. (2012)
Gamification (GAM)	Application of elements of the games domain to change human behaviors in non-game environments.	Deterding et al. (2011)
Streaming Intention (INT)	Intention to use the technology.	Venkatesh et al. (2003)
Use (U)	Effective use of the technology.	Venkatesh et al. (2003)

Facilitating conditions can be defined as the consumers' perceptions of the resources and support available to perform a behavior (Venkatesh et al., 2003). In the scope of this study, it is framed as consumers' perceptions of the resources and support available to listen to songs on TikTok and identify them to listen to them in streaming platforms.

When identifying a song from a short TikTok snippet requires greater effort, users may need other resources or support to identify it and to find it on streaming platforms. If the support is not available, the likelihood of using TikTok as a source for music discovery may decrease, as the process is perceived as less convenient or beneficial. The presence of resources or support allows users to be exposed to and interact with TikTok content, enhancing familiarity and interest in songs and, therefore, increasing the likelihood of transferring listening behavior to streaming platforms. This is called the mere exposure effect, a phenomenon studied by psychologists where people develop a liking for a product due to repeated exposure. It is, however, important to note that this happens in an inverted u-shape, meaning that interest and engagement rise with exposure up to an optimal point, after which they begin to decline (Sguerra et al., 2022).

Therefore, the following hypothesis will be tested:

H1: Facilitating conditions have a positive impact on streaming use.

From a cognitive perspective, the availability of facilitating conditions reduces the cognitive effort required to use TikTok, making the experience of discovering music through TikTok more pleasurable and enjoyable (Agarwal & Karahanna, 2000). Hedonic motivation can derive from the content itself, but the environment in which it is experienced also plays an important role in creating and maintaining this motivation. If users feel that the necessary resources and support are available, they tend to enjoy the experience more (Venkatesh et al., 2012). In other words, the presence of support and technological resources can enhance the pleasure users get from using the system.

Taking this into account, the following hypothesis is proposed:

H2: Facilitating conditions have a positive impact on hedonic motivation.

Gamification is defined as the application of elements of the games domain to change human behaviors in non-game environments (Deterding et al., 2011). Gamified features, such as badges, leaderboards, and points, fulfil users' needs for entertainment, achievement, and social interaction (Uses and Gratifications Theory - Katz, Blumer & Gurevitch, 1973), while also fostering intrinsic motivation through competence, relatedness, and autonomy (Self Determination Theory - Deci & Ryan, 1985).

Gamification can increase perceived discovery value by making TikTok more engaging and goal-oriented, which motivates users to seek out new songs, artists, or trends. Research on gamification shows that it can also promote exploratory behavior and sustained engagement, which will enhance discovery (Hamari, Koivisto, & Sarsa, 2014).

Hence, the following hypothesis will be tested:

H3: Gamification has a positive impact on perceived discovery value.

Social influence is defined as the extent to which consumers perceive that other people believe they should use a particular technology. Several theories and frameworks, such as the Theory of Reasoned Action, the Theory of Planned Behavior and UTAUT, identify social influence as one of the factors influencing technology use and behavior. Since creators and peers can have a different kind of influence on the user, this construct was divided into creator influence and peer influence.

As users see creators interacting and engaging with music or music related content on TikTok, their perception of the value of the platform in discovering and consuming music will increase. In digital music contexts, discovery has become a key component of perceived performance benefits (Morris & Powers, 2015; Wikström, 2013). When creators endorse or repeatedly use music on TikTok, users may interpret this as evidence that the platform effectively facilitates meaningful discovery. Creators also influence perceived discovery value since their videos expose users to content that they might not otherwise encounter (Tafesse & Dayan, 2023).

Therefore, the following hypothesis will be tested:

H4: Creator influence has a positive impact on perceived discovery value.

According to earlier studies, social modeling and observational learning can greatly lower perceived complexity because people rely on the experiences of others to comprehend how technologies work (Bandura, 1986). Studies show that consumers' trust in using technologies can be increased by creators' familiarity, genuineness, and frequent exposure, which lowers perceived effort (Abidin, 2020; Tafesse & Dayan, 2023). Creators can influence users' opinions about a system, impacting effort expectancy (Venkatesh et al., 2003). Users are more likely to view TikTok and its music discovery features as user-friendly when creators actively promote and showcase music-related content.

Therefore, the following hypothesis is proposed:

H5: Creator influence has a positive impact on effort expectancy.

The mainstream use of social media tools facilitates communication between peers and the creation of groups with similar interests. It has been reported that «online users are 6 times more likely to discover new music because of their peers in an online community, when compared to discovery in the absence of those peers» (Garg et al., 2011). More recent studies have shown that users tend to interact with people with similar tastes and behavior in what regards music discovery and consumption, as it happens with other areas of life (Di Bona et al., 2022).

Hence, the following hypothesis will be tested:

H6: Peer influence has a positive impact on streaming intention.

Hedonic motivation is defined as the fun or pleasure derived from using a technology (Venkatesh et al., 2012), and it is seen as a predictor of the intention to use a technology.

Studies have shown that several factors that build hedonic motivation, such as joy and curiosity, positively influence the behavioral intention to use TikTok (Rahayu, Nastiti, Arthajanvian, 2025).

Considering this, the following hypothesis will be tested:

H7: Hedonic motivation has a positive impact on streaming intention.

Performance expectancy is defined as the degree to which a user believes that using a system improves performance (Venkatesh et al., 2003).

In this study, this construct was adapted to Perceived Discovery Value, referring to the extent to which users feel that TikTok enables them to discover new, relevant, or personally meaningful content. According to TAM and UTAUT, performance-related perceptions are strong predictors of behavioral intention and continued use of technological systems, as individuals tend to engage more with platforms they perceive as useful in supporting their goals. Within the context of TikTok, perceived discovery value is particularly relevant, as users' sense of added value through discovering appealing or new content can intensify their intention to use the platform.

Therefore, the following hypothesis is proposed:

H8: Perceived discovery value has a positive impact on streaming intention.

Effort expectancy is the degree of ease associated with consumers' use of technology (Venkatesh et al., 2003). An application that demands less effort to be used by people tends to be better accepted by users (Davis, 1989). However, several studies indicate that the importance of effort expectancy diminishes as individuals gain experience with digital technologies. Research on TAM2 and UTAUT has shown that as users become more familiar with technological systems, the perceived effort required to learn or operate a new application becomes less relevant compared to other determinants of use, such as usefulness, habit, or social influence (Venkatesh & Davis, 2000). Given that most users today have extensive experience interacting with digital applications, effort expectancy is expected to have a comparatively smaller positive influence on the intention to use of a platform such as TikTok.

Hence, the following hypothesis will be tested:

H9: Effort expectancy has a positive impact on streaming intention.

Behavioral intention is the intention to use a technology (Venkatesh et al., 2003). This is a predictor of the effective use of a technology.

In the case of TikTok and music-streaming platforms, it is expected that, as the intention to stream songs increases, the use of music platforms to listen to songs will also increase, provided that the user has access to these platforms.

Considering this, the following hypothesis will be tested:

H10: Streaming intention has a positive impact on streaming use.

Considering the constructs and the hypotheses presented above, the following model was built:

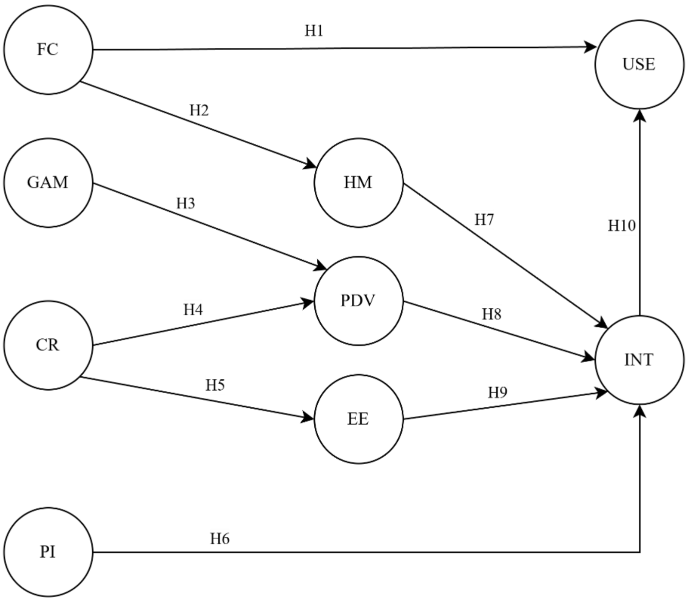

FIGURE 1 – Proposed Model

4. RESEARCH METHODOLOGY

Data was collected using an online questionnaire, created with the Google Forms platform, available in Portuguese and in English. Items associated to each construct were adapted from other studies and applied to the context of TikTok and music-streaming platforms. Most of these items were rated using a Likert Scale ranging from 1 to 7, where 1 means "Strongly Disagree" and 7 means "Strongly Agree". In the case of constructs measuring use and frequency of behaviors, specifically Use, the corresponding items were also rated from 1 to 7, where 1 represents "Never" and 7 represents "Many times per day". Finally, the last question was optional and open-ended, allowing people to express any opinions on TikTok, music-streaming platforms, and the way they are related. Annex 1 contains the items utilized in the questionnaire.

The online questionnaire was used in order to reach a larger number of people from different backgrounds, while also allowing for quicker and easier monitoring and visualization of results. Google Forms also provides a spreadsheet of the answers, which is useful for the next step of analysis using appropriate software tools.

5. RESULTS

In order to examine the relationships between the model constructs, Structural Equation Modeling (SEM) was applied, using the Partial Least Squares (PLS) approach. This enables analysis of the validity of the measurement model, while also being useful in checking the reliability of the structural model.

This method was implemented using the SmartPLS software. This software contains tools to model the relationship between constructs, while also providing values such as the Fornell-Larcker criterion, the Variance Inflation Factor (VIF), among others. The relevance of these measures in evaluating the measurement model and the structural model will be explained in this section. The results will be interpreted in the discussion.

5.1. Characterization of the sample

The research was directed at people who are familiar with music-streaming and social media platforms. The survey was shared mainly on social media, which made it possible to reach people with different backgrounds, such as ages, education levels and genders. The goal was to understand how people interact with TikTok and in which way their engagement with the social media platforms affects their music discovery and consumption.

In order to characterize the sample and understand possible differences in demographic groups regarding the study, 4 demographic questions were included in the questionnaire: age, gender, education level and country of residence. The remaining questions are available in Appendix 1. Additionally, an optional question where the respondent could provide their opinions regarding the study topic was also available.

The final dataset contains 314 responses. An overview of the demographics of the respondents is available in Appendix 2. It is interesting to note that 210 of the respondents identified as female, which represents 66.88% of the sample. From the remaining 104 respondents, 99 identified as male, corresponding to 31.53% of the sample, and 5 people identified as other. Regarding age, the average is around 24 years old, with the youngest respondent being 12 years old and the oldest 65 years old. Regarding education level, 40.13% had a bachelor's degree, 31.53% had obtained high school education and 20.06% had a master's degree, with only 7.64% with below high school education and only 2 people, less than 1% with a PhD. Lastly, 51 different countries were present in the sample.

The three most common countries are the United States of America, with 85 people representing 27.07% of the sample, Portugal with 36 respondents, corresponding to 11.46%, and the United Kingdom, with 31 and 9.87% of the sample.

A cluster analysis using the K-means algorithm was conducted to identify distinct user profiles based on the mean scores of the study constructs. All variables were standardized prior to clustering to ensure equal weighting. Based on the elbow method and silhouette score, a three-cluster solution was retained, as it offered an appropriate balance between statistical adequacy and interpretability.

The three clusters exhibit distinct profiles across the analyzed constructs, as shown in Figure 2. Cluster 1 represents highly engaged users, characterized by consistently high scores across all constructs and strong reliance on TikTok for music discovery and subsequent streaming behavior. This cluster is predominantly female, with an average age of 23. Cluster 2 reflects a more passive user segment, with lower construct scores and weaker behavioral intentions toward streaming platforms. This cluster is predominantly male, with an average age of 27. Cluster 3 includes moderately engaged users who perceive some value in music discovery and display conditional streaming intentions. This group is mostly female, with an average age of 23. Overall, the findings confirm the presence of heterogeneous user segments in TikTok-driven music discovery. This analysis, as well as correlation metrics, can be consulted in the link: https://github.com/nonotrigo/tiktokstreaming.

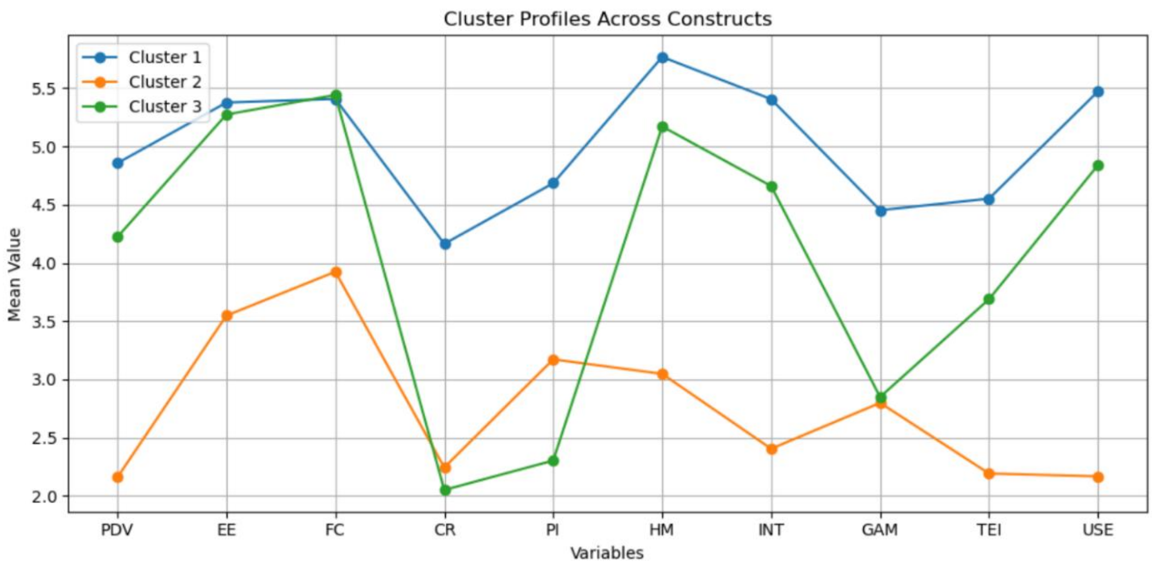

FIGURE 2 – Cluster Analysis Results

5.2. Measurement Model Evaluation

Some ways of analyzing the model's construct reliability and validity include Cronbach's alpha and the Composite Reliability. Both are used to measure the internal consistency of a model. However, the first considers all indicators as equally reliable, while the latter takes into account the loadings of different indicators. For this reason, it is sometimes seen as more appropriate for evaluating PLS models, which prioritize indicators according to their reliability. The model is considered consistent when these values are higher than 0.7, meaning that the items of each construct are correlated and reliable (Henseler et al., 2009).

The values of these measures for each construct and respective items are available in Appendix 3. For every construct, the values are higher than 0.7, therefore ensuring reliability and validity.

The reliability of each indicator can be verified by analyzing the Outer Loadings of each item. These show how correlated an item is with the respective construct. An item's loading should be higher than 0.7 in order to be considered a reliable item in evaluating the respective construct (Henseler et al., 2009).

The Outer Loadings present in Appendix 3 show that most of the items are reliable, with only 3 items with an outer loading lower than 0.8.

The validity of the measurement model can be divided into convergent validity and discriminant validity. Convergent validity ensures that the indicators of a construct represent the same construct and are unidimensional. Discriminant validity ensures that indicators of different constructs are different enough to not relate to the same construct and are not unidimensional.

The convergent validity of the model is measured using the Outer Loadings and the Average Variance Extracted (AVE) of each indicator. For a construct to be considered valid, its AVE should be higher than 0.5, meaning that the construct explains more than half of the variance of its items. The outer loadings should be higher than 0.7, as mentioned above.

The values of the AVE and the Outer Loadings are present in the Appendix III. All of the constructs have values for the AVE higher than 0.5, showing convergent validity. The Outer Loadings are also high, as stated before. Therefore, both of these measures indicate good convergent validity.

The discriminant validity of the model can be evaluated using the Fornell-Larcker criterion (Fornell & Larcker, 1981). This criterion says that, for a model with discriminant validity, each construct should have higher variance with the respective items than with any other construct. This means that the AVE for each construct should be higher than the square of the correlations with the other constructs. Another way to check for discriminant validity of a model is through the cross-loadings of each indicator, and according to this method, these should be lower than the outer-loadings (Hair et al., 2014).

The values for the Fornell-Larcker criterion are presented in Table II. The values in the diagonal of this table correspond to the square root of the AVE for each construct. It is possible to see that these values are higher than the correlation of each construct with the others, for every construct. Appendix IV contains the values for the cross loadings. Since these are lower than the loadings for every construct, both methods make it possible to state that the model has good discriminant validity.

TABLE II – Fornell-Larcker criterion

	CR	**EE**	**FC**	**GAM**	**HM**	**INT**	**PDV**	**PI**	**USE**
CR	**0.925**								
EE	0.178	**0.905**							
FC	0.205	0.727	**0.755**						
GAM	0.343	0.199	0.156	**0.920**					
HM	0.321	0.502	0.483	0.294	**0.942**				
INT	0.359	0.562	0.540	0.314	0.752	**0.929**			
PDV	0.344	0.574	0.496	0.273	0.723	0.723	**0.877**		
PI	0.481	0.098	0.128	0.308	0.210	0.271	0.156	**0.949**	
USE	0.274	0.513	0.492	0.232	0.659	0.741	0.656	0.176	**0.942**

5.3. Structural Model Evaluation

When creating a structural model, it is important to check for collinearity between constructs, since this can affect the results of the regression. Variance Inflation Factor (VIF) is a measure that helps to verify that this problem is not present in a model. When there is no collinearity between variables, this value should be under 5 (Sarstedt et al., 2017).

The results indicate that there is no collinearity present between the constructs, since every VIF value is under 5. Specifically, the values are all smaller than 2.4 (Table III).

TABLE III – Inner VIF

	CR	**EE**	**FC**	**GAM**	**HM**	**INT**	**PDV**	**PI**	**USE**
CR		1.000					1.134		
EE						1.529			
FC					1.000				1.411
GAM							1.134		
HM						2.190			
INT									1.411
PDV						2.394			
PI						1.046			
USE									

Another important aspect to evaluate the structure of the model is the Coefficient of Determination (R^2). This coefficient measures the variance explained in each of the endogenous constructs and serves as a measure of the model's explanatory power. The R^2 can vary from 0 to 1, where a higher value indicates higher degree of explanatory power. A value of 0.75 is considered high, 0.5 is a medium value, and 0.25 is a small value (Sarstedt et al., 2017).

The structural model presented in Figure 2 shows the R^2 values. Creator influence explains 3.2% of effort expectancy ($\hat{\beta}$ = 0.178, p < 0.005). Creator influence ($\hat{\beta}$ = 0.284, p < 0.001), together with gamification ($\hat{\beta}$ = 0.176, p < 0.005), explain 14.6% of perceived discovery value. It is also possible to explain 23.3% of hedonic motivation by facilitating conditions ($\hat{\beta}$ = 0.483, p < 0.001). Hedonic motivation ($\hat{\beta}$ = 0.427, p < 0.001), perceived discovery value ($\hat{\beta}$ = 0.303, p < 0.001), effort expectancy ($\hat{\beta}$ = 0.161, p < 0.001) and peer influence ($\hat{\beta}$ = 0.118, p < 0.001) can explain 66.3% of the intention. Lastly, facilitating conditions ($\hat{\beta}$ = 0.130, p < 0.01) and intention ($\hat{\beta}$ = 0.671, p < 0.001) explain 56.1% of the use of music-streaming platforms.

Therefore, it is possible to conclude that the model is capable of explaining the latent variables and all paths are supported with some predictive impact. In particular, intention and use are explained in large proportion through the constructs.

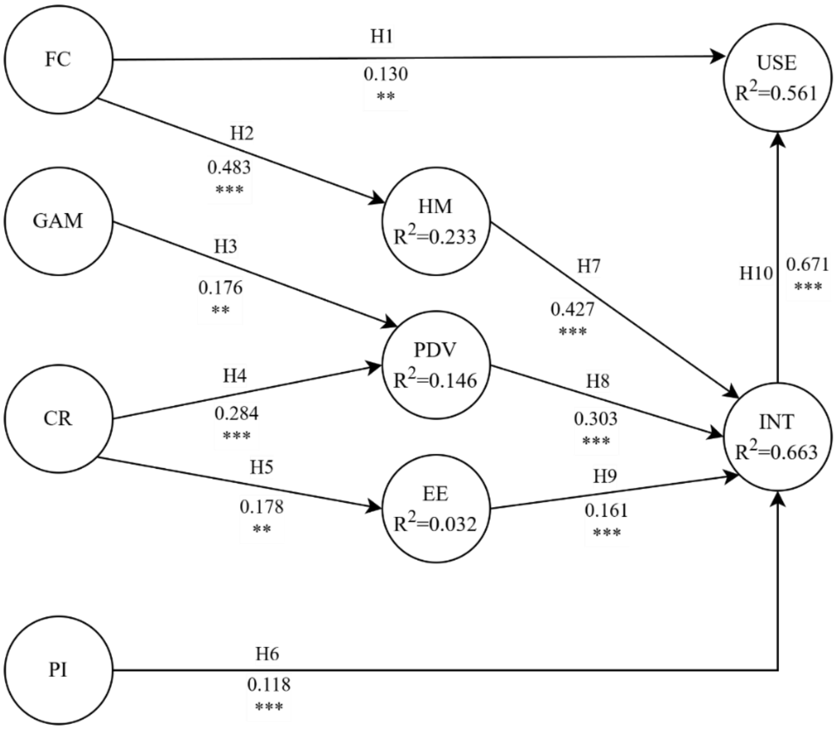

FIGURE 3 – Proposed Model with R² values

* significant with p < 0.05; ** significant with p < 0.01; *** significant with p < 0.001

The F² score measures the contribution of the exogenous variables to the endogenous variables, allowing to understand the effect of each variable in the other. The effect is considered large when F² is higher than 0.350, medium when the score is between 0.150 and 0.350 and small when it is between 0.020 and 0.150. (Aparicio et al., 2021).

The values for the F² of the model's hypotheses are available in Table IV. All the hypotheses have scores larger than 0.020, therefore every hypothesis is supported. The biggest score is 0.726 for hypothesis 10, showing that streaming intention has a large effect on streaming use. Hypothesis 2 and 7 have a medium F^2 score. Therefore, it is possible to conclude that facilitating conditions have a medium effect on hedonic motivation ($F^2 = 0.305$) and hedonic motivation has a medium effect on streaming intention ($F^2 = 0.248$). The remaining hypotheses have an F-score higher than 0.020 and lower than 0.150, meaning that the effect exists, but is considered small.

TABLE IV – Betas, P-Values, F^2, Effect, and Decision

Hypothesis	Beta	P-values	F^2	Effect	Decision
H1: Facilitating conditions have a positive impact on streaming use.	0.130	0.007	0.027	Small	Supported
H2: Facilitating conditions have a positive impact on hedonic motivation.	0.483	0.000	0.305	Medium	Supported
H3: Gamification has a positive impact on perceived discovery value.	0.176	0.003	0.032	Small	Supported
H4: Creator influence has a positive impact on perceived discovery value.	0.284	0.000	0.083	Small	Supported
H5: Creator influence has a positive impact on effort expectancy.	0.178	0.002	0.033	Small	Supported
H6: Peer influence has a positive impact on streaming intention.	0.118	0.001	0.040	Small	Supported
H7: Hedonic motivation has a positive impact on streaming intention.	0.427	0.000	0.248	Medium	Supported
H8: Perceived discovery value has a positive impact on streaming intention.	0.303	0.000	0.114	Small	Supported
H9: Effort expectancy has a positive impact on streaming intention.	0.161	0.001	0.051	Small	Supported
H10: Streaming intention has a positive impact on streaming use.	0.671	0.000	0.726	Large	Supported

5.4. Discussion

The p-values for all hypotheses are under 0.007 and the F^2 scores are between 0.027 and 0.726. Therefore, it is possible to conclude that the 10 hypotheses are supported.

Hypothesis 1, regarding the impact of facilitating conditions on streaming use, is supported, with a p-value of 0.07 and an F^2 score of 0.027. It is possible to state that facilitating conditions affect streaming use. This is aligned with previous research, where facilitating conditions were shown to impact the usage behavior of information technology (Venkatesh et al., 2012). However, this effect is considered small, with a $\hat{\beta}$ of 0.130. Previous studies regarding different industries, such as e-government services (Alshehri et al., 2012) and education (Abbad et al., 2021), found that facilitating conditions have a stronger effect on use, with a $\hat{\beta}$ of 0.48 for the first case and 0.309 for the second.

In hypothesis 2, facilitating conditions are shown to impact hedonic motivation with a greater magnitude than the previous case. The F^2 score of 0.305, the p-value of 0, and the $\hat{\beta}$ of 0.483 support this hypothesis. In a previous study, regarding the adoption of mobile learning among undergraduates, facilitating conditions were also shown to have an impact on hedonic motivation, although the coefficient, $\hat{\beta}$ = 0.138, was not as high as in this study (Kaisara et al., 2022). This suggests that in the case of TikTok and music-streaming platforms, facilitating conditions have a bigger impact on hedonic motivation.

Hypothesis 3 studies the effect of gamification on perceived discovery value. This hypothesis is supported with a coefficient of 0.176, a p-value of 0.003 and a score of 0.032, making it possible to state that gamification has a small effect on perceived discovery value of TikTok when it comes to music. Since perceived discovery value is a construct derived from performance expectancy, there are no studies about the relation between gamification and this construct. However, a previous study on e-commerce found that gamification affordances affect the perceived value of technology (Budiman et al., 2025). Another research synthesized different studies and showed that gamification increases perceived values such as emotional, functional, and social values (Jia et al., 2024).

The hypotheses regarding creator influence, H4 and H5, are also supported, showing that creators can impact the perceived discovery value and effort expectancy of TikTok in discovering and consuming music. According to the coefficients and the F^2 values, creator influence has a stronger effect on perceived discovery value ($\hat{\beta}$ = 0.284 and F^2 = 0.083) than on effort expectancy ($\hat{\beta}$ = 0.178 and F^2 = 0.033). Corroborating H4, studies have shown that TikTok creators allow users to discover songs aligned with their taste or shift it through the discovery of new content, therefore increasing TikTok's perceived discovery value (Ranff & Degener, 2023). It is also interesting to mention that music discovery through creators is seen by some people as more authentic than algorithmic recommendations, and therefore more valuable, meaning that less effort is necessary to discover relevant content (Bubnova, 2024).

Hypothesis 6, regarding the impact of peer influence on streaming intention, is supported with a coefficient of 0.118 and F^2 of 0.040. This makes it possible to state that peers, such as friends and family, have a small impact on the intention to use TikTok to discover and consume music on other platforms. It was not possible to find research regarding peer influence, as creator and peer influence are generally aggregated under the social influence construct. However, the impact of general social influence is further validated by the UTAUT model, which considers it one of the predictors of the intention to use a certain technology (Venkatesh et al., 2003). Another study about music-streaming services found that social influence has a positive effect on purchase intention and attitude towards paid streaming services (Chen et al., 2018).

The positive influence of hedonic motivation on streaming intention is corroborated by hypothesis 7 of the study, with a coefficient of 0.427 and a F^2 of 0.248. Therefore, it is possible to state that hedonic motivation has a medium effect on streaming intention. Similarly to peer influence in the previous hypothesis, this construct was added as one of the predictors of usage intention in the UTAUT2 framework (Venkatesh et al., 2012). Studies regarding music reached a similar conclusion (Hampton-Sosa, 2019; Barata & Coelho, 2021), although in the second, the effect of hedonic motivation on streaming intention was considered small, with $\hat{\beta}$ = 0.09.

The effect of perceived discovery value on streaming intention is also validated by the study. Hypothesis 8, with a $\hat{\beta}$ = 0.303 and F^2 = 0.114, makes it possible to verify the positive influence of perceived discovery value on the intention to stream songs discovered on TikTok. As stated previously, this construct was adapted from performance expectancy, and there are no studies regarding its impact on streaming intention. However, in the case of music-streaming platforms, it has been stated that performance expectancy is one of the strongest predictors of behavioral intention, with $\hat{\beta} = 0.218$ (Barata & Coelho, 2021).

Effort expectancy is another construct that influences streaming intention, according to hypothesis 9. This hypothesis was supported ($p = 0.001$), with a coefficient of 0.161 and $F^2 = 0.051$, proving the small effect of effort expectancy on streaming intention. The same study mentioned previously regarding music-streaming platforms corroborated this connection, but it reached the conclusion that this effect is smaller, with $\hat{\beta} = 0.073$.

The last hypothesis studies the impact of streaming intention on the use of technology. The effect between these two dimensions is the largest one found in this study, with $\hat{\beta} = 0.671$ and $F^2 = 0.726$. This is in alignment with the UTAUT model, which considers the intention to use technology as one of the main predictors of its actual use (Venkatesh et al., 2012). Another study also confirms that intention is crucial in predicting actual use of TikTok (Ta et al., 2025).

The last question of the survey was open ended, to allow people to express their opinions about TikTok and music-streaming platforms. The responses were mainly positive, with most users enjoying TikTok and considering it a powerful tool for music discovery. Some limitations mentioned by the respondents were the promotion of trending content instead of personal preferences and the lack of integration between TikTok and music-streaming platforms. It is possible that some people are unaware of the "Add to Music App" functionality, which allows a seamless transition from TikTok to streaming platforms. Lastly, some users prefer to use TikTok only for watching videos, relying on YouTube and music-streaming platforms for music discovery and consumption.

6. CONCLUSION

The rapid evolution of digital platforms has transformed how music is discovered, consumed, and promoted. In this context, TikTok has emerged as a central actor in the music industry, blurring the boundaries between social media engagement and music-streaming behavior. This dissertation aimed to investigate how TikTok influences music-streaming habits through an extended UTAUT2-based framework to examine the mechanisms through which social media engagement translates into streaming intention and behavior.

Using a quantitative approach and data collected from 314 respondents across 51 countries, this study provides empirical evidence that TikTok plays a meaningful role in shaping music-streaming behavior. The proposed research model, consisting of 9 constructs and 10 hypotheses, was validated through PLS-SEM analysis, showing strong reliability, convergent validity, and discriminant validity.

The findings demonstrate that streaming intention is the strongest predictor of actual use of music streaming platforms, confirming the central role of behavioral intention in technology acceptance theories (H10). This intention is strongly influenced by hedonic motivation (H7), followed by perceived discovery value (H8), effort expectancy (H9), and peer influence (H6). Facilitating conditions were found to influence both streaming use (H1) and hedonic motivation (H2). Creator influence positively affected perceived discovery value (H4) and effort expectancy (H5). Additionally, gamification was shown to positively influence perceived discovery value (H3).

From a theoretical perspective, this study contributes to literature in several ways. First, it extends the UTAUT2 framework to a cross-platform context, integrating social media use and music-streaming behavior in the model. Second, it introduces perceived discovery value as an adaptation of performance expectancy, offering a construct that is particularly relevant in algorithm-driven content environments. Third, the disaggregation of social influence into creator influence and peer influence provides a more nuanced understanding of how different social actors shape technology-related behavior.

These contributions help bridge existing gaps in the literature by explicitly modeling TikTok's role not merely as a promotional channel, but as a behavioral driver that influences downstream consumption on music-streaming platforms.

The results offer important practical implications for multiple stakeholders. For music-streaming platforms, improving integration with TikTok and enhancing discovery-related features may increase user engagement and conversion from discovery to streaming. For artists and record labels, the findings reinforce the importance of creator-driven promotion and authentic engagement on TikTok as a means of boosting streaming outcomes. Independent artists, in particular, can leverage TikTok's discovery dynamics to reach new audiences without relying solely on traditional industry gatekeepers. For platform designers, the positive effects of hedonic motivation and gamification suggest that enjoyable, low-friction user experiences are essential to sustaining engagement and encouraging music-related behaviors across platforms.

The limitations of the study include the fact that the data is based on self-reported measures, which may be subject to response bias. Another restriction is the fact that the sample consists mainly of younger users and students, and therefore, the study's results may not apply to older populations.

Future research could address these limitations by employing longitudinal designs or behavioral data from platforms themselves. Additionally, further studies could explore differences across genres, cultural contexts, or levels of user engagement, with cluster analysis similar to the one performed in this study, using multigroup analysis, as well as compare TikTok with other short-form video platforms such as Instagram Reels or YouTube Shorts. Investigating artist-side perspectives or revenue implications would also provide valuable extensions to the present research.

In conclusion, this dissertation provides empirical evidence that TikTok significantly influences music-streaming habits by shaping how users discover, perceive, and engage with music. As social media and streaming platforms continue to converge, understanding these dynamics becomes increasingly important for both academic research and industry practice. TikTok is not merely a trend-driven entertainment platform, but a powerful driver of music discovery and consumption in the digital age.

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APPENDICES

Appendix 1- Questionnaire

Construct	Items	Author
Creator Influence (CR)	CR1: TikTok creators and influencers who are important to me think that I should stream certain songs. CR2: TikTok creators and influencers who influence my behavior think that I should stream certain songs. CR3: TikTok creators and influencers whose opinions I value prefer that I stream certain songs.	(Venkatesh et al., 2003)
Effort Expectancy (EE)	EE1: Finding songs I discover on TikTok on my music streaming platform is easy for me. EE2: It is clear and understandable how to find a song used in a TikTok video in a music streaming platform. EE3: I find it easy to discover a song used in a TikTok video in a music streaming platform. EE4: It is easy for me to become skillful at discovering a song used in a TikTok video in a music streaming platform.	(Venkatesh et al., 2003)
Facilitating Conditions (FC)	FC1: I have the resources necessary (links, search, Shazam) to find songs I discover on TikTok. FC2: I can get help from others when I have difficulties accessing a song I discover on TikTok. FC3: I have the knowledge necessary to find songs I discover on TikTok. FC4: TikTok is compatible with music streaming platforms I use.	(Venkatesh et al., 2003)
Gamification (GAM)	GAM1: The presence of a badges system would increase my engagement with songs I find on TikTok. GAM2: The presence of badges would make me feel more likely to do actions to obtain them. GAM3: The presence of a leaderboards system would increase my engagement with songs I find on TikTok. GAM4: The presence of leaderboards on TikTok would make me do actions to get to a specific position. GAM5: The presence of a points system would increase my engagement with songs I find on TikTok. GAM6: The presence of points would make me feel more likely to do actions to obtain them.	(Deterding et al., 2011)
Hedonic Motivation (HM)	HM1: Using TikTok to discover music is fun. HM2: Using TikTok to discover music is enjoyable. HM3: Using TikTok to discover music is very entertaining.	(Venkatesh et al., 2012)
Streaming Intention (INT)	INT1: I intend to stream songs I discover on TikTok in the future. INT2: I plan to continue streaming songs I discover on TikTok frequently. INT3: I will always try to stream songs I discover on TikTok in my daily life.	(Venkatesh et al., 2003)

Perceived Discovery Value (PDV)	PDV1: I find discovering music through TikTok useful in my daily life. PDV2: Using TikTok helps me discover music more quickly. PDV3: Using TikTok to discover music increases my productivity.	(Venkatesh et al., 2003)
Peer Influence (PI)	PI1: Friends and family who are important to me think that I should stream certain songs. PI2: Friends and family who influence my behavior think that I should stream certain songs. PI3: Friends and family whose opinions I value prefer that I stream certain songs.	(Venkatesh et al., 2003)
Use (U)	U1: I stream songs I discovered on TikTok. U2: I add songs I discovered on TikTok to a playlist. (1= Never, …, 7= Many times per day)	(Venkatesh et al., 2003)

Appendix 2- Questionnaire Results

	Type	Quantity	Percentage
Gender	Female	210	66.88%
	Male	99	31.53%
	Other	5	1.59%
	Total	314	100%
Age	< = 25	231	73.57%
	> 25	83	26.43%
	Total	314	100%
Education Level	Below High School	24	7.64%
	High School	99	31.53%
	Bachelor's Degree	126	40.13%
	Master's Degree	63	20.06%
	PhD	2	0.64%
	Total	314	100%
Top 5 Countries	USA	85	27.07%
	Portugal	36	11.46%
	UK	31	9.87%
	Netherlands	27	8.60%
	Germany	22	7.01%

Appendix 3- Outer Loadings, Composite Reliability and AVE

Construct	Item	Outer Loading	Composite Reliability	Cronbach's Alpha	AVE
CR	CR1	0.916	0.926	0.916	0.855
	CR2	0.942			
	CR3	0.915			
EE	EE1	0.865	0.928	0.926	0.818
	EE2	0.903			
	EE3	0.936			
	EE4	0.913			
FC	FC1	0.774	0.759	0.744	0.569
	FC2	0.630			
	FC3	0.854			
	FC4	0.744			
GAM	GAM1	0.912	0.969	0.964	0.846
	GAM2	0.923			
	GAM3	0.932			
	GAM4	0.923			
	GAM5	0.924			
	GAM6	0.904			
HM	HM1	0.950	0.937	0.936	0.887
	HM2	0.949			
	HM3	0.926			
INT	INT1	0.924	0.923	0.920	0.863
	INT2	0.961			
	INT3	0.901			
PDV	PDV1	0.923	0.860	0.849	0.769
	PDV2	0.898			
	PDV3	0.806			
PI	PI1	0.942	0.954	0.946	0.901
	PI2	0.952			
	PI3	0.954			
U	U1	0.951	0.889	0.873	0.887
	U2	0.932			

Appendix 4- Cross Loadings

	CR	EE	FC	GAM	HM	INT	PDV	PI	U
CR1	**0.916**	0.198	0.218	0.348	0.321	0.345	0.340	0.423	0.276
CR2	**0.942**	0.164	0.196	0.303	0.291	0.341	0.323	0.450	0.262
CR3	**0.915**	0.125	0.146	0.297	0.272	0.306	0.285	0.466	0.216
EE1	0.162	**0.865**	0.632	0.213	0.529	0.539	0.559	0.146	0.493
EE2	0.146	**0.903**	0.650	0.157	0.388	0.452	0.463	0.045	0.415
EE3	0.140	**0.936**	0.675	0.190	0.435	0.526	0.518	0.049	0.456
EE4	0.195	**0.913**	0.672	0.157	0.454	0.506	0.528	0.106	0.485
FC1	0.098	0.566	**0.774**	0.085	0.308	0.401	0.336	0.109	0.410
FC2	0.215	0.429	**0.630**	0.158	0.315	0.343	0.308	0.085	0.262
FC3	0.107	0.682	**0.854**	0.058	0.384	0.463	0.382	0.068	0.404
FC4	0.210	0.499	**0.744**	0.178	0.437	0.411	0.452	0.122	0.389
GAM1	0.349	0.187	0.164	**0.912**	0.285	0.310	0.293	0.270	0.240
GAM2	0.318	0.222	0.159	**0.923**	0.277	0.313	0.269	0.319	0.247
GAM3	0.328	0.147	0.116	**0.932**	0.263	0.261	0.239	0.283	0.192
GAM4	0.314	0.154	0.101	**0.923**	0.248	0.278	0.215	0.284	0.156
GAM5	0.311	0.183	0.149	**0.924**	0.279	0.297	0.239	0.279	0.226
GAM6	0.267	0.199	0.162	**0.904**	0.264	0.267	0.236	0.260	0.200
HM1	0.314	0.474	0.450	0.296	**0.950**	0.729	0.718	0.229	0.653
HM2	0.258	0.464	0.468	0.280	**0.949**	0.713	0.669	0.168	0.617
HM3	0.336	0.481	0.447	0.255	**0.926**	0.683	0.655	0.195	0.590
INT1	0.296	0.560	0.537	0.260	0.719	**0.924**	0.656	0.237	0.707
INT2	0.347	0.524	0.520	0.290	0.724	**0.961**	0.693	0.258	0.707
INT3	0.360	0.479	0.443	0.328	0.651	**0.901**	0.666	0.261	0.649
PDV1	0.304	0.556	0.514	0.220	0.701	0.709	**0.923**	0.128	0.631
PDV2	0.242	0.559	0.462	0.209	0.712	0.671	**0.898**	0.093	0.647
PDV3	0.369	0.383	0.313	0.300	0.471	0.508	**0.806**	0.197	0.432
PI1	0.437	0.124	0.133	0.294	0.188	0.237	0.131	**0.942**	0.157
PI2	0.430	0.061	0.123	0.303	0.193	0.248	0.152	**0.952**	0.168
PI3	0.497	0.093	0.110	0.281	0.214	0.283	0.158	**0.954**	0.176
U1	0.214	0.508	0.503	0.193	0.638	0.747	0.619	0.159	**0.951**
U2	0.310	0.456	0.418	0.248	0.601	0.641	0.617	0.175	**0.932**