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Emotions at Play: Understanding the Role of Emotions and Technology Acceptance in Diverse Music Consumption.

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1 Introduction

The past few years have witnessed an exceptional transformation in the music industry, more intense than at any other time since its birth in the 1890s. Indeed, in the past, music has been commercialized through selling physical or digital goods: wax cylinders, piano rolls, vinyl records, cassettes, CDs, downloads. However, the main way through which the industry makes revenues has recently changed. Spotify, Apple Music, Amazon Music, Tidal, YouTube, and other equivalent platforms have redefined how audiences engage with music. Now, streaming serves as the main income source for recorded music (Passman, 2019).

According to IPFI's Engaging with Music 2022 report, 74% of people interviewed consume music through licensed audio streaming services (subscription and ad-supported). This trend is only expected to grow, as confirmed by an increase of 10% in time spent listening to music on subscription audio services in 2022, thus reaffirming audience's strong attraction to streaming. Moreover, IPFI's report shows that, on average, people spend 20.1 hours listening to music each week. Therefore, we can comfortably say that our lives are accompanied by a soundtrack and that technological advancements have not only changed how we consume said soundtrack, but also how the music affects us emotionally.

Consequently, the goal of this dissertation is to explore through a PLS-SEM analysis the complex relationship between positive and negative emotions and diverse music consumption in the context of the rapidly evolving music industry. Moreover, we will investigate the moderating effects of the factors of the TAM in relation to the recommender systems of music streaming services, perceived ease of use and perceived usefulness, on the relationships between emotions and diverse music consumption.

To achieve our objective, we start with a brief overview of the history of the music industry in Chapter 2, with a particular focus on the rise of music streaming services and their recommendation systems. Then, we examine the various music consumption trends and how the digital age has shaped and transform them.

The background theory for the moderation variables within our theoretical framework is presented in Chapter 3. It explores models of technology diffusion and acceptance, which can help us understand why and how new technologies, such as music streaming platforms, become popular and accepted by users.

Chapter 4 looks closely at how emotions affect the music-listening experience. It starts with an introduction on emotional theory and moves on by exploring how emotions shaped our music experience. Then, it gives the background theory on the Uses and Gratification approach, which will help us understand the relationship between music and its listeners, as well as the emotional motivations behind music consumption. Finally, it explains the role that positive and negative emotions have when people listen to music.

Chapter 5 is where we reveal the results of our own investigation. Starting from the development of hypotheses, we discuss our research methodology, present our results and findings, and discuss their theorical and practical implications.

Overall, this dissertation offers a thorough examination of the contemporary landscape of music consumption. By integrating theoretical models with empirical research, it aims to contribute a thorough understanding of the relationship between emotions, new technologies, and diverse music consumption.

2 Music Industry 2.0: How Technology is Constantly Revolutionizing the Business

2.1 *A Brief History of the Music Industry*

The music industry and technology have always been strongly intertwined, and this bond has only gotten stronger over time. Technology has influenced and transformed how we make, consume, and enjoy music, from the early days of recorded sound to the emergence of digital music distribution and streaming services. To show how close the relation between music and technology is, Figure 1 depicts the revenue growth trend of the American music industry from 1973 to 2022 broken down into the different storage formats of music.

The invention of the phonograph by Thomas Edison in 1877 was one of the earliest examples of how technology can affect the music industry. This groundbreaking invention enabled the recording and replaying of sound for the first time, revolutionizing the music business. Suddenly, music could be captured and distributed with a larger audience, opening the door for the birth of record labels (Columbia Records, for example, was founded in 1889) and the commercialization of music (Aldrich, 2007).

The introduction of radio broadcasting in the early 20th century further transformed the music industry by allowing music to be broadcasted to millions of people at the same time. By far the cheapest form of entertainment, radio broadcasting was way more entertaining than everything most people were used to. Consequently, its popularity skyrocketed during the late 1920s and into the early 1930s. By 1934, radios had become a common good, with approximately 60% of American homes owning one (Scott, 2008).

Simultaneously, sales of the wax cylinder used in phonographs were diminishing due to the introduction of the flat disc phonograph (Aldrich, 2007).

The 1950s brought on the next age of innovations. This decade was marked by significant advances that lowered the manufacturing costs of vinyl records. This fall in production costs promoted the development of a competitive market. It was during this period that all the major entities in today's recording industry joined the market, taking advantage of the cost-efficiency. Both RCA and Columbia emerged as major players in the music recording industry throughout the 1950s. During this decade, a lot more record companies came into the market, but they eventually transformed into a few big corporations by merges and acquisitions. Consequently, these major labels were able to exploit economies of scale by vertically integrating the whole recording and publishing process (Bielas, 2013).

The digital revolution started in the 1980s had a profound impact on the industry, transforming once again the way music was produced, distributed, and consumed. The development of digital recording technology allowed artists to create and manipulate music in new ways. At the same time, the rise of the compact disc (CD) led to cheaper production costs and, consequently, caused a decrease in music prices, thus allowing consumers to increase their spendings of musical content.

The launch of the Music Television Network, known as MTV, marked another significant development of the 1980s. It was the first network showcasing music videos 24/7, and by 1984 had reached enormous popularity and had successfully extended its reach and impact to a wider audience (Bielas, 2013).

In the 1990s, the music industry saw the most interesting breakthroughs. Indeed, at the start of the decade, the CD became the main format through which audiences purchased and consumed music, causing a decline in cassettes sales and the near extinction of vinyl (RIAA). CDs saw their peak in popularity in 1999, the year Napster was launched. A peer-to-peer (P2P) file sharing application, Napster enabled anyone to access music at no cost over the Internet through MP3 files. Music had officially moved to the Internet. Record labels, however, initially failed to adapt to this new technology, and recorded music revenues started inevitably falling.

At the start of the 21st century, many digital marketplaces started emerging to counter the illegal download of free music. Supported by copyright holders, in 2003 Apple launched the iTunes store, which by the next year already offered 1,000,000 songs to its users (Aldrich, 2007). However, between 2000 to 2010, US recorded music revenues were almost cut in half, due to the steep decline in physical sales and digital sales not taking over as expected (RIAA).

This dire situation began improving after the launch of Spotify, an audio streaming subscription service. Founded on the idea that convenient access and the ability to listen music at any time are essential, not personal ownership, Spotify and its competitors allow users to access a wide library of music by paying a monthly subscription (Bielas, 2013).

This new technology and approach to music was ultimately successful, as in 2015 global revenues started growing again, after more than a decade of decline, and they continue to do so these days. Indeed, in 2022, global recorded music revenues reached US$26.2 billions, with streaming accounting for about 67% of the overall market up from a 65.5% share the prior year (IFPI, 2023).

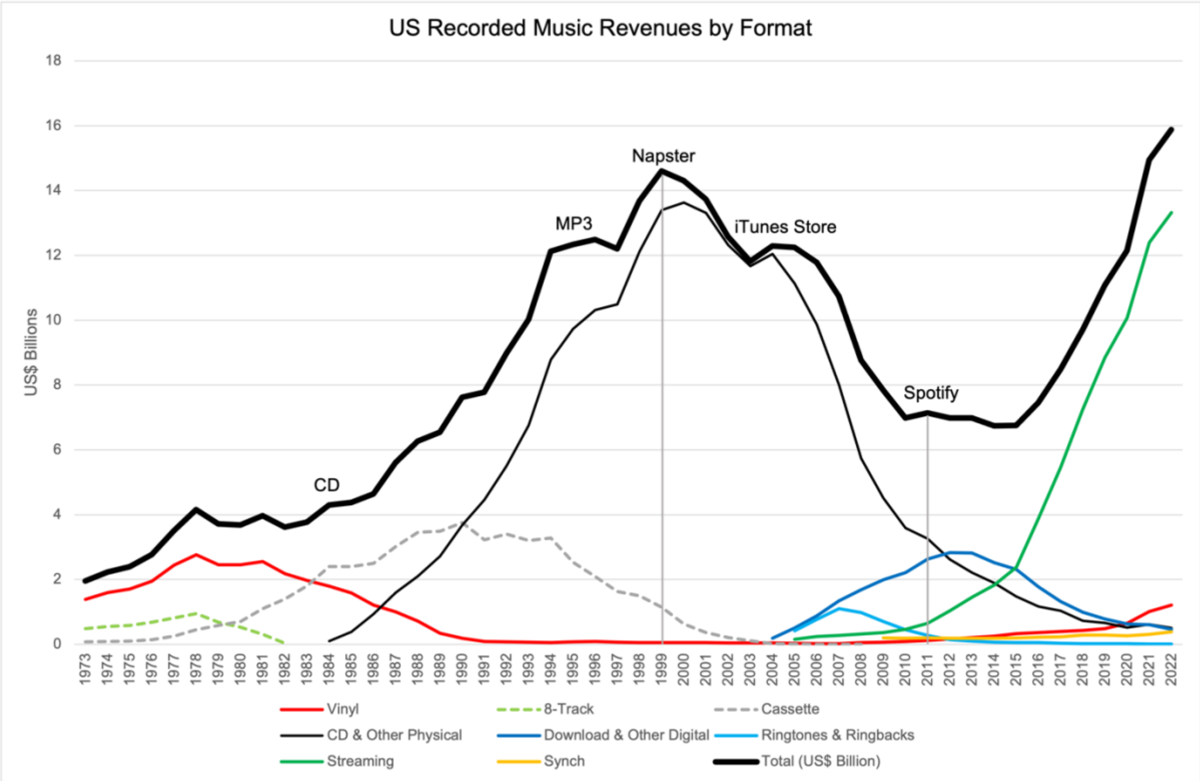

Figure 1. *U.S. Recorded Music Revenues by Format (Source: RIAA)*

2.2 *A New Era of Music Consumption: Streaming Services*

Today, music streaming services have been around for more than a decade, with the introduction of Spotify in 2008 marking a notable industry milestone. These platforms operate on a relatively recent business strategy that essentially offers two forms of service: registration of a free account, where users are subject to advertisements and various limitations (freemium model), or, in contrast, users pay a monthly fee, granting them unrestricted access to the service (premium model). This latter method contributes substantially to a significant portion of the industry's revenue (Barata et al., 2021).

This new business model had and continues to have a profound impact on the music industry. Indeed, in 1999, when the music business was at its peak, the typical CD buyer spent around $45 per year. Today, the average fee per subscriber is approximately $7 (due to student and family discounts), implying that listeners are spending around $84 per year. This is nearly double the $45 of CD purchases of 1999. Furthermore, prior to streaming, the average CD buyer quit visiting record stores in their early twenties. Nowadays, streaming services attract users from all age groups. This means that streaming isn't only bringing in higher revenue per user, but it's also attracting a larger demographic than ever before (Passman, 2019).

Spotify, Apple Music, Amazon Music, and YouTube Music are among the major players in the music streaming market, as shown in Figure 2.

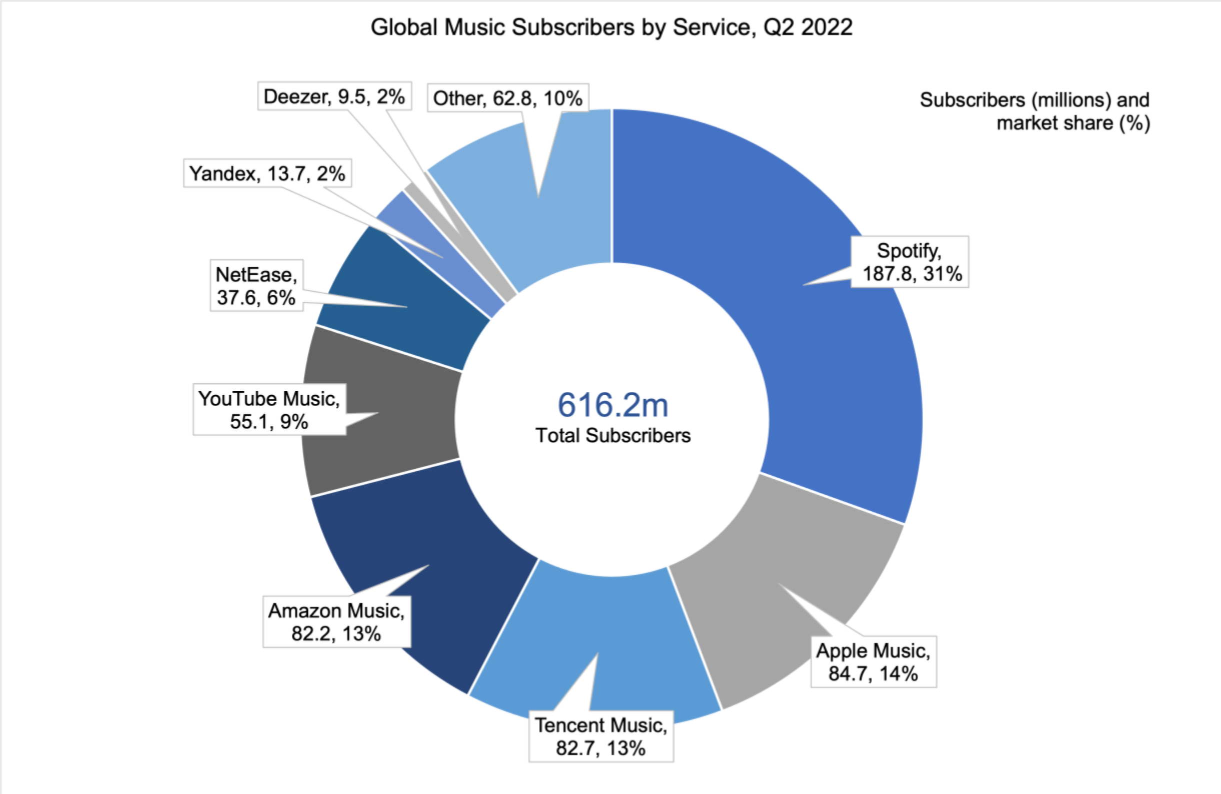

***Figure 2**. Global Music Streaming Subscription Market, Q2 2022 (Source: MIDiA Research)*

Each of these services provides a similar experience, allowing users to browse a large music library, create playlists, and discover new artists. However, because of competition, many services started to offer exclusive content, such as live recordings, concerts, interviews, to attract more users.

For example, Apple Music offers most of its catalog in lossless audio and Spatial Audio with Dolby Atmos for a more immersive experience. Moreover, Apple Music Sing offers users a karaoke-like experience directly on the platform. Users can also listen to live radio stations, both exclusive to Apple Music (such as Music 1 and Music Hits) and local broadcasters (such as BBC Radio 1 and RTL 102.5).

Spotify and Amazon Music, on the other hand, both let artists sell merchandising on their platforms. They also both offer users a free, ad-supported version, contrary to Apple Music.

Despite being the primary way that people consume music, music streaming services still face some challenges. Indeed, streaming platforms have been subject to criticisms since their rise to popularity. The critiques moved can be grouped in three sets of claims:

- The first concerns the “per-stream” rates paid to artists and right holders, who claim that the rates are damaging them especially in financial terms;

- The second is that the current system tends to reinforce unfair industrial power structures, specifically the prevalent dominance of major record labels and the select group of musical superstars closely allied with them;
- The final set of claims addresses changes in the distribution of rewards in music: it states that the rewards have become more unjust over time, and that it is now more difficult for artists to make a decent income from recorded music than before music streaming services (Hesmondhalgh, 2021).

To shed light on these problems, especially those of fairness and digital revenues, some artists have gone as far as pulling their music from streaming services: for example, Thom Yorke took down from Spotify Atoms for Peace's and his solo music between 2013 to December 2017.

Another big challenge for music streaming services comes from the fierce competition from within the industry, but also from other forms of media, such as podcasts, video streaming, and audio books. Consequently, several platforms have begun offering video content and exclusive podcasts through partnerships with big creators: for example, according to the New York Times, Spotify has paid Joe Rogan $200 million to obtain the exclusive rights to his podcast.

Regardless of these challenges, there are still growth opportunities in the music streaming market, particularly through the integration of emerging technologies such as Web3, Artificial Intelligence, Virtual Reality and Augmented Reality.

Web3 application could be the solution to some of the challenges faced by music streaming services, in particular that of unfair compensations to artists. Indeed, blockchain technology has the potential to aid artists in releasing and monetizing their work, allowing for direct distribution to their fan base. Some companies, such as Audius, have already started moving in this direction. According to their website, Audius is "a decentralized, community-owned and artist-controlled music-sharing protocol", with the objective of providing a blockchain-based alternative to existing streaming platforms.

On the other hand, Artificial Intelligence (AI) has potential to improve numerous aspects of music streaming services, particularly in music discovery and recommendation systems. At the time of writing this, Spotify has already started rolling out its new AI DJ feature. Through the combination of Spotify's personalization technology, generative AI through the use of OpenAI technology, and a dynamic AI voice platform, Spotify claims that this new feature "knows you and your music taste so well that it can choose what to play for you".

Finally, AR and VR technologies open up new possibilities for immersive and interactive music. By embedding these technologies into their platforms, streaming services could let viewers "attend" live events from the comfort of their homes. Already in 2015, U2 and Apple Music partnered for a VR music video of the band's "Song for Someone", so that fans could feel directly on stage with U2. Alternatively, AR and VR could be used to facilitate music promotion, discovery, and creation. The clearest illustration of this may be seen on YouTube, where popular musicians have started to upload music videos with a 360-degree scannable environment.

In conclusion, music streaming services have become some of the biggest players in the music business by offering users access to millions of songs at their fingertips. However, new and emerging technologies have the potential to revolutionize the music streaming industry, opening up new opportunities for innovation and growth. So, to ensure long-term success and sustainability in the always evolving world of music consumption, all stakeholders must be able to react, adapt and embrace these technologies.

2.3 *The Evolution of Recommendation Systems in Music Streaming Services*

With the ability to offer personalized suggestions and improve user experiences across a variety of industries, including e-commerce, social media, and entertainment, recommendation systems have come to be an essential component of digital platforms.

These systems gather users' preferences, which are either clearly expressed or deduced by interpreting users' actions, and then provide suggestions for items to be of use to a user such as products, music, news articles, among others. Hence, recommendations are personalized, so that different users receive diverse suggestions (Ricci et al., 2022).

The main objective of a recommendation system is to boost revenue for the platform. To achieve this, recommendation systems have common operational and technical goals:

- Relevance, since users are more inclined to engage with items they perceive as interesting;
- Novelty, because recommended systems are perceived more helpful when the suggestions are something that users have not seen in the past;
- Serendipity, which adds an element of surprise to the items recommended;
- Increasing recommendation diversity, which ensures users do not lose interest due to repeated suggestions of similar items.

Moreover, from users' perspective they help increase the overall satisfaction with the platform; thus, improving loyalty and increasing sales. While, from the businesses' perspective, recommender systems can offer insights into user preference and aid in further customizing the user experience.

There are two main approaches for building recommender systems, which rely on two different kinds of data: collaborative filtering methods use user-item interactions, like ratings, while content-based recommender methods use utilize the attribute information about the users and items, such as relevant keywords or textual profiles.

Collaborative filtering can be either user-based, where recommendations are based on the ratings provided by like-minded users of a target user, or item-based, where the system suggests items like those the user has previously interacted with.

In content-based filtering, the item's content information is combined with the user ratings and buying behavior.

Some recommender systems develop hybrid systems by fusing these two different methods. Hybrid systems can combine the benefits of multiple recommender system types to provide techniques that work more effectively in a wide variety of settings (Aggarwal, 2016).

Recommendation systems are one key factor contributing to the success and popularity of music streaming services as they help users navigate the vast music catalog that the platforms offer. Most common music items include artists, albums, tracks, and playlists.

The music industry has several distinctive traits that set music recommender systems (MRS) apart from other kinds of recommender systems:

- Duration of consumption: due to the relatively short duration of songs, users can form opinions on music items in a significantly shorter time compared to, for instance, movies.
- Catalog size: today, some music streaming platforms have more than 100 million songs in their catalogs, while catalogs of video streaming platforms are far smaller. Consequently, scalability is way more important in the music domain.
- Different representations and abstraction levels: unlike movie recommender systems, which normally suggest individual items within a specific category (e.g., movies or series), MRS have the capability to recommend music items in various formats and modalities (e.g., songs, music videos, etc.). Moreover, music recommendation can have different levels of granularity (e.g., at the level of artist, album, or song).
- Repeated consumption: users frequently listen to the same piece of music repeatedly, sometimes even back-to-back. Conversely, other forms of media are often only

consumed once (e.g., movies). This suggests that a user could not only tolerate, but rather enjoy, suggestions of items they are already familiar with.

- Sequential consumption: music items are frequently consumed in sequence (e.g., in a playlist), differing from movies or books.
- Passive consumption: music is typically listened to passively, serving as background noise, which might impact the accuracy of preference indicators.
- Importance of content: explicit rating data is relatively rare in the music domain. As a result, compared to the techniques used in other domains, research on MRS tends to focus more heavily on content descriptions of items. Thus, content-based recommendation approaches are far more important in the music industry than in other businesses.

Hence, a basic functionality of MRS is to generate personalized recommendation lists, relying on the user's past interactions with the platform. The items that constitute these lists must not only align with the user's preferences or requirements, but also meet a variety of quality criteria:

- Similarity vs. diversity: the music in the recommendation list should be similar to the user's favorite tracks and exhibit some degree of resemblance among themselves.
- Novelty vs. familiarity: a recommendation list should include content the user is already familiar with, such as known songs or songs by a known artist, not least because familiarity appears to be crucial for evoking strong emotional reactions in listeners. On the other hand, a recommendation list should typically also include a certain number of items that are novel to the target user.
- Popularity, hotness, and trendiness: these aspects are not unique to a user, but global measures, typically computed on system level. Several commercial MRS include track lists generated by a popularity-based recommender as a standard feature to reduce cold start or keep users informed of trending music. Even though these lists are not personalized, they allow to engage users by acting as an entry point to the system and as a basic discovery tool.
- Serendipity: central to this aspect is the notion of unexpectedness, which is often understood as being unfamiliar or well outside of the user's regular music taste.
- The sequential coherence of music items in the recommendation list (Schedl et al., 2021).

To further enhance user experience and satisfaction, MRS should continue to evolve particularly through the integration of new and emerging technologies.

For instance, various studies in the field of music psychology have revealed that short-term preferences are affected by users' emotional, physical, or social context. By integrating contextual information, such as user location, time of day, and listening device, could provide more pertinent recommendations can be tailored to the user's specific situation. Thanks to the rise in employment of Internet of Things (IoT) devices, nowadays these contextual data can be easily retrieved (Lozano Murciego et al., 2021).

Artificial Intelligence can also be useful in the interpreting extensive data sets, converting raw data into insightful knowledge, thus further improving the user experience. For example, since user preferences shift due to the evolving of personal tastes, individual experiences or trends in popularity, recommender systems should move past the traditional assumption that user preferences are static. This can be achieved through the adoption of methods that can manage temporal dynamics and can depict changes (Zhang et al., 2020).

By exploring these and other emerging technologies, researchers and especially businesses can continue improving user experiences and satisfaction, thus further increasing users' loyalty to their platforms and, consequently, revenues.

2.4 *A Comprehensive Analysis of Diverse Music Consumption*

By enabling users to more easily access and explore a wide catalog of music, the rise of streaming platforms has significantly impacted music consumption patterns (Datta et al., 2017). Diversity is a fundamental characteristic of a listener's content consumption, and it defines how broad the set of pieces of content a user engage with is. On one end of this spectrum, a user may merely interact with a tiny portion of the platform's catalog by consuming very similar content. On the other extreme, a user may engage with a bigger portion of the catalog by consuming pieces of content that are very different from each other. Every user's consumption falls somewhere along this range, regardless of whether the decision was made consciously (Anderson et al., 2020).

Prior to the digital revolution, discovering new music required a considerable expense of time and money. Indeed, listeners had to travel to record stores and invest significant sums to buy albums in search of new and unknown artists. Other ways of discovering new music included going to shows of local bands, high-priced magazines, or friends living in other cities and countries (Tepper et al., 2009).

Today, when discovering new music, users of music streaming services usually have two options: they can either discover music with user-guided search and exploration or through algorithmic recommendations – both of these alternatives require way less resources in terms of time and money (Anderson et al., 2020). However, Anderson et al. (2020) found that algorithm recommendations lead to less varied music consumption and, as consumers stray from these recommendations, their consumption diversity increases. This finding seems to be in contradiction with Bello and Garcia's study (2021), which determines that the top charts on streaming platforms have become more diverse since 2017 across many nations, but Hesmondhalgh et al. (2023) conclude that both works support the idea that diversity increases with human intervention.

This notion is further confirmed by the fact that social media platforms vastly contribute to the diffusion of diverse music across nations. Social media is used by both musicians and fans to exchange music from many cultural traditions, generating a sense of connectivity and community throughout the world. Social media sites like Facebook, Twitter, and Instagram enable users to find new artists and participate in discussions about new music, which promotes the consumption of a variety of musical genres (Baym, 2018).

In conclusion, even if algorithmic suggestions and streaming platforms have revolutionized the accessibility of varied music, social media and human interaction continue to play a critical role in guaranteeing a truly diverse and rewarding musical experience. In order to build a more diverse and integrated global music landscape going ahead, it is crucial for the music business, artists, and consumers to find a balance between technology-driven and human-guided discovery.

3 Technology Diffusion and Acceptance Theories

Technology diffusion and acceptance are necessary steps of innovation and technological development, as they explain how new technologies are embraced and used by individuals, organizations, and communities. As technology continues to reshape our reality at an outstanding rate, consistently revolutionizing how we live, work, and interact, it is increasingly important to have a thoroughly understanding of the processes and elements affecting technology adoption and acceptance.

3.1 *Technology Diffusion Theories*

According to Stoneman and Battisti (2010), technology diffusion can be defined widely as "the process by which the market for a new technology changes over time and from which production and usage patterns of new products and production processes result".

The Diffusion of Innovation Theory was first studied by the French sociologist Gabriel Tarde in 1903, but was popularized by the work of Rogers, with his book *Diffusion of Innovations*, published in 1962 (Kaminski, 2011).

In his book, Rogers provides a heuristic framework for analyzing the diffusion of innovations (Fleiter et al., 2013), and he starts with some important definitions:

- Diffusion is defined as "the process by which an innovation is communicated through certain channels over time among the members of a social system";
- Consequently, communication refers to "the process in which participants create and share information with one another in order to reach a mutual understanding";
- And finally, an innovation is "an idea, practice, or object that is perceived as new by an individual or other under unit of adoption". Newness depends on the perception of the potential adopter.

Then, the four principal components of innovation diffusion are the innovation itself, communication channels, time, and social system (Rogers, 1983).

Through the element of time, researchers have been successful in categorizing adopter categories and to plot diffusion curves. Starting from prior research that showed innovation adoption as a normal, bell-shaped curve, Rogers (1983) plotted the cumulative number of adopters, which resulted in an s-shaped curve, as shown in Figure 3. This s-shaped diffusion curve suggests that, in the early diffusion stage of an innovation, the proportion of users to prospective adopter is quite low (Fleiter et al., 2013). We, then, see the curve continuing to rise, accelerating to a maximum until half of the system's users have adopted, and gradually slowing as the few remaining individuals adopt. Rogers (1983) argues that this normal s-shaped curve is due to the diffusion effect, which he defines as “the cumulative increasing degree of influence upon an individual to adopt or reject an innovation, resulting from the activation of peer networks about the innovation in social systems”. In other words, as early innovators “spread the word” about the innovation, more and more individuals become aware of it until it becomes increasingly improbable that users will encounter remaining potential adopters. Thus, adoption of an innovation is “the result of human interaction through interpersonal networks” (Rogers, 1983).

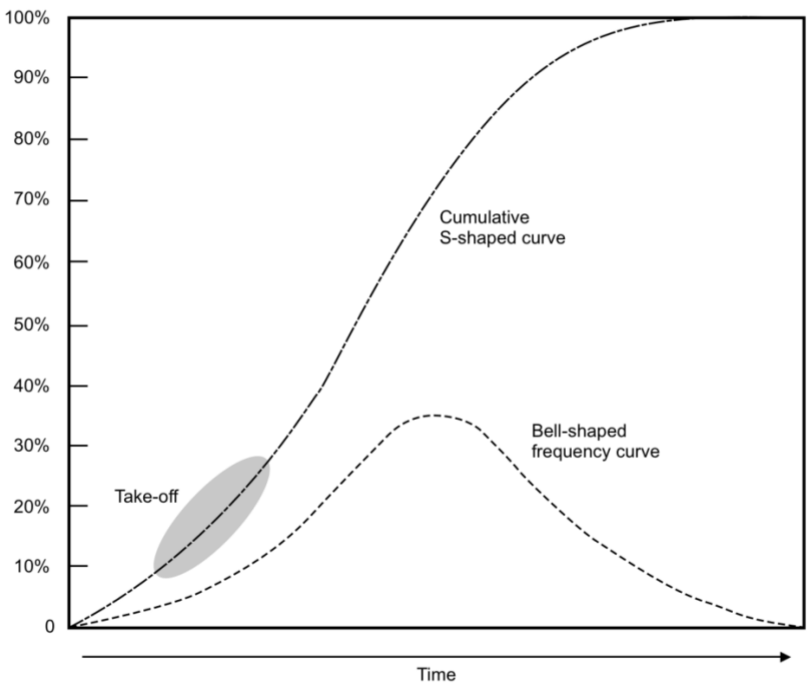

Figure 3. *The bell-shaped frequency curve and the s-shaped cumulative curve for an adopter distribution (Source: Rogers, 1983)*

Users become adopters through the innovation-decision process, which is defined as “the process through which an individual (or other decision-making unit) passes from first knowledge of an innovation, to forming an attitude toward the innovation, to a decision to adopt or reject, to implementation of the new idea, and to confirmation of this decision” (Rogers, 1983). So, the process is made of five stages (see Figure 4):

1. Knowledge: individual becomes aware of an innovation but does not possess comprehensive information about it.
2. Persuasion: when an individual becomes curious about the innovation.
3. Decision: when an individual decides to either embrace or discard the innovation.
4. Implementation: when an individual makes extensive use of the innovation.

5. Confirmation: when an individual resolves to continue using the innovation, but the decision may be reversed if he or she is exposed to conflicting information about the innovation.

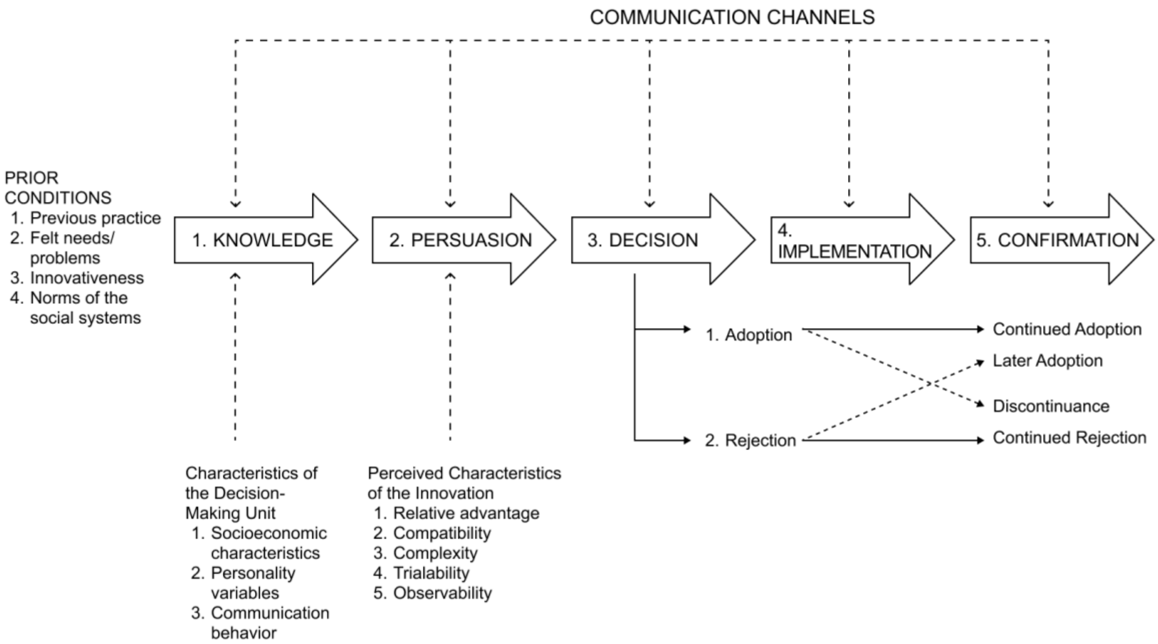

Figure 4. *Innovation-decision process (Source: Rogers, 1983)*

Rogers (1983) goes on outlining five categories of adopters of an innovation: innovators, early adopters, early majority, late majority, and laggers. He also estimated the percentages of each category, which are closely matching those found in a normal bell-curve.

Finally, he also describes the various attributes of innovation and how the perception of these characteristics can contribute to the prediction of their rate of adoption. According to Rogers (1983), while they are theoretically distinct, each of them is somewhat empirically connected to the other four. So, the five attributes of innovation are:

1. Relative advantage: the extent to which an innovation is considered superior to the concept it replaces. Since potential adopters want to know how much better a new concept is with respect to the status quo, relative advantage is a strong predictor for an innovation's adoption rate.
2. Compatibility: the extent to which an innovation aligns with the values, previous experiences, and desires of potential adopters. A new idea may or may not be in line with (1) sociocultural values and beliefs, (2) previously introduced concepts, or (3) client demands for innovations. This feature has a positive correlation with an innovation's rate of adoption.

3. Complexity: the level of difficulty perceived by potential adopters in understanding and using an innovation. It is inversely proportional to the rate of an innovation's adoption..
4. Trialability: the extent to which an innovation can be experimented with on a small scale. The more experimentable an innovation is, the less uncertainty potential adopters face. Therefore, the trialability of an innovation has a positive correlation with its rate of adoption.
5. Observability: the extent to which an innovation's results may be seen by other individuals. While certain innovations are hard to express to express to someone else, these people can quickly witness and understand the effects of such ideas. This feature is positively associated with an innovation's rate of adoption.

However, despite its popularity, Rogers' Diffusion of Innovation Theory has its limitations, for which it has also been criticized: for example, Karahanna et al. (2005) argue that it fails to consider the cultural and social values in which the diffusion takes place.

Moreover, Bass (1969) argued that because Rogers' discussion is mainly literary, it is sometimes difficult to separate its hypotheses from the conclusions. Consequently, he contributes to Rogers' concept with the development of a theory of timing of initial purchase of new consumer products.

Together, these theories give us a valuable understanding of how new technologies spread and are adopted by individuals.

3.2 *Technology Acceptance Theories*

3.2.1 Theory of Reasoned Action

Initially developed in 1975 for sociological and psychological purposes, the Theory of Reasoned Action (TRA) has subsequently become the founding approach to investigate one's attitude towards using information technologies (IT) (Taherdoost, 2018).

Fishbein and Azjen's (1975) conceptual framework is concerned with the relations between beliefs, attitudes, intentions, and behavior (Figure 5). In particular, TRA suggests that an individual's intentions are a function of certain beliefs:

- Some beliefs influence an individual's perception of a particular behavior, as attitude is related to the conviction that engaging in such behavior will lead to specific outcomes.
- Other are normative beliefs, which encompasses beliefs about what significant others think the individual should or should not do in relation to the behavior in question. Coupled with the motivation to comply with any given referent, these beliefs form what

is called “subjective norm”: a major determinant of a person’s intention to carry out the behavior.

So, intention is a function of a person’s attitude toward the behavior and his or her subjective norm (Fishbein et al., 1975). This behavior should be “volitional, systematic, and rational” (Taherdoost, 2018).

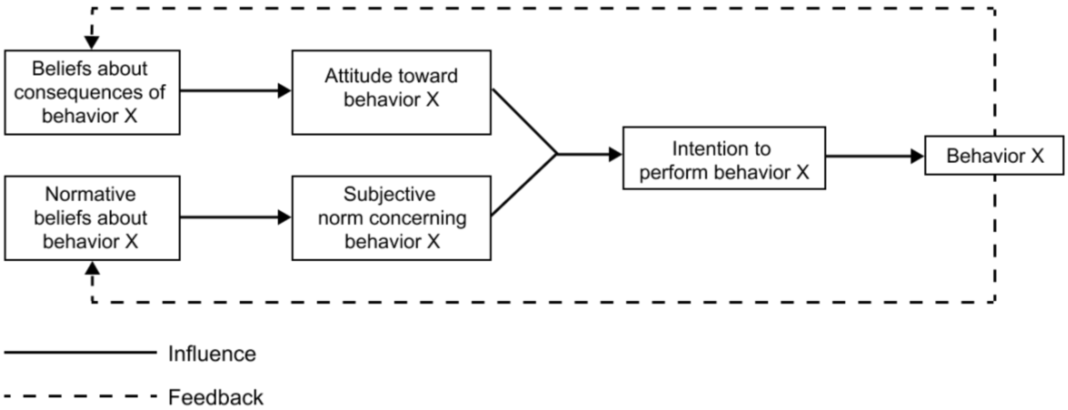

Figure 5. *Conceptual framework of the Theory of Reasoned Action (Source: Fishbein and Azjen, 1975)*

3.2.2 Theory of Planned Behavior

As TRA is a general model, not aimed at a specific behavior or technology, many researchers have extended and deepened its subject.

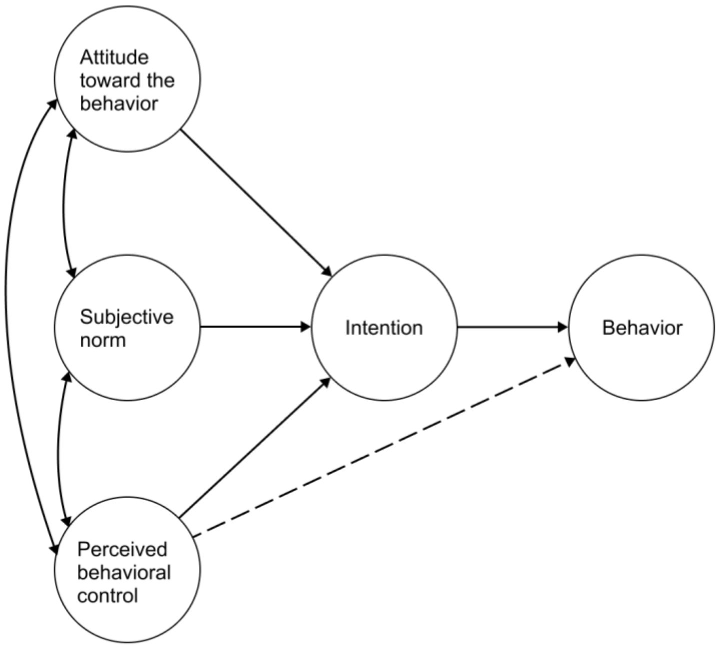

Figure 6. *Theory of planned behavior (Source: Azjen, 1991)*

Indeed, in 1985, Azjen extended the TRA conceptual framework by introducing a new variable: perceived behavioral control (PBC). Azjen argues that this extension, called Theory of Planned

Behavior (TPB), was necessary to deal with the TAR's limitations in handling behaviors over which individuals have no volitional control.

In this model, PBC is defined as an individual's perception of how easy or difficult performing the behavior of interest will be. Moreover, it can vary across situations and actions (Azjen, 1991). Thus, according to TPB, behavioral intention and perceived behavioral control can be used together to predict behavioral achievement (Figure 6).

3.2.3 Technology Acceptance Model

Then, in 1986, Fred Davis introduced another variant of TRA, the Technology Acceptance Model, which became the most prominent model used when describing users' acceptance and usage of technology. Teo (2011) defines technology acceptance as "a user's willingness to employ technology for the tasks it is designed to support".

The TAM came into being due to the rapid growth of end-user computing in the early 1980s and had two main objectives: "to improve the understanding of user acceptance processes", and "to provide the theoretical basis for a practical 'user acceptance testing' methodology that would enable system designers and implementors to evaluate proposed new systems prior to their implementation" (Davis, 1986).

To achieves those objectives, the TAM provides the theoretical basis for a practical "user acceptance testing" methodology. Hence, as shown in Figure 7, Davis suggests that the attitude toward using a given system is a function of perceived usefulness (PU) and perceived ease of use (PEOU), with PEOU having a direct effect on PU. This relationship between PEOU and PU is given by the fact that, all else being equal, a system easier to use will result in a higher consumption of the system itself. Davis, then, goes on by defining perceived usefulness as "the degree to which an individual believes that using a particular system would enhance his or her job performance" (Davis, 1986). Consequently, a system with a higher perceived usefulness is one for which the user feels there is a favorable use-performance connection (Davis, 1989).

On the other hand, perceived ease of use is "the degree to which an individual believes that using a particular system would be free of physical and mental effort" (Davis, 1986). Effort is subsequently described as a limited resource that a person can devote to the numerous tasks for which he or she is responsible (Davis, 1989).

Despite being widely accepted, Davis' model has been subject to criticisms over the years. In particular, Bagozzi (2007) has pointed out various limitations with the TAM in his commentary titled "The Legacy of the Technology Acceptance Model and a Proposal for a Paradigm Shift". He argues that researchers have ignored crucial determinants of decision and action, favoring a more straightforward model. He noted large gaps between intents and behavior, as well as between PU and PEOU on the one hand, and intention on the other. Moreover, discuss how further research has only broaden the model, failing to deepen it in the sense of explaining PU and PEOU, or of introducing new variables to describe how the existing ones produce the effects they do. Concluding, Bagozzi (2007) offers a model in order to provide the groundwork for a paradigm change. He argues that, by using this approach, the theory of technology acceptance is deepened, and goes on suggesting ways for better understanding how, when and why decisions are made in different technological applications.

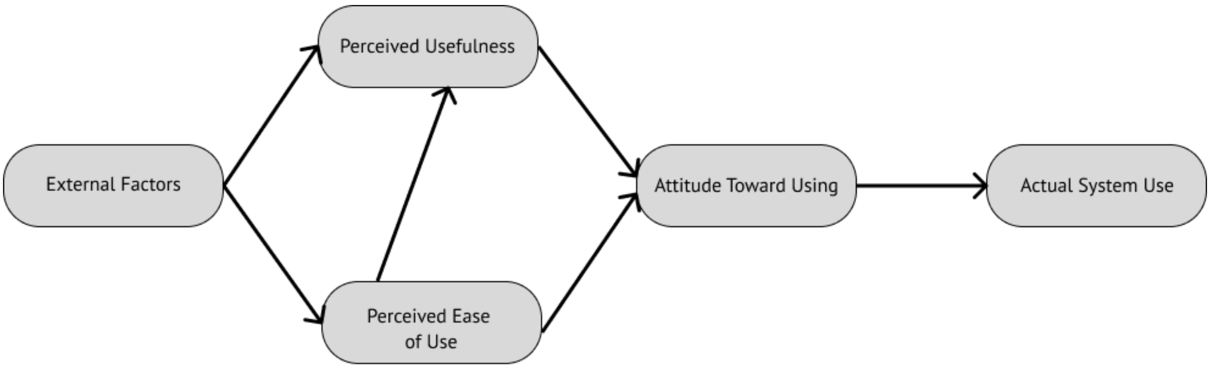

Figure 7. *Technology Acceptance Model (Source: Davis, 1986)*

As Bagozzi (2007) has pointed out, since 1986, researchers have expanded the Technology Acceptance Model over the years. For example, Mathieson (1991) compared the Theory of Planned Behavior to the Technology Acceptance Model. His results show that both models are suited to predict behavioral intention well, but that Davis's model was "easier to use" as it uses a standard set of instruments (Moore et al., 1996).

Another example is the development of the Extended Technology Acceptance Model (TAM2). Adopting constructs from TRA and TPB models, this extension of TAM explains PEOU and PU in terms of social influence (image, subjective norms, and voluntariness) and cognitive instrumental processes (job relevance, output quality, and result demonstrability) (Venkatesh et al., 2000). By including some constructs from older theories, TAM2 will increase the overall performance of TAM (Momani et al., 2017).

3.3 *Integrating Technology Acceptance Model with Innovation Diffusion Theory*

Rogers and Davis argue that the Diffusion of Innovations (DOI) and the Technology Acceptance Model (TAM) offer the most significant theoretical approaches to literature on innovation adaptation and are also widely used by researchers to examine a range of technological innovations adoption. Both models operate on the assumption that adopters evaluate innovations on the basis of their perceived traits, suggesting that innovations boasting appealing characteristics are more likely to gain acceptance (Al-Rahmi et al., 2019). Indeed, scholars usually associate the relative advantage feature of DOI to the perceived usefulness of TAM, and, at the same time, consider the complexity feature of DOI to be extremely similar to the perceived ease of use concept of TAM. This suggests that these models confirm each other's findings as well as complementing each other (Chen et al., 2002). So, researchers believe that combining TAM and DOI could lead to the creation of a stronger model with satisfactory results (Wu et al., 2005). For example, as in TAM compatibility is not explored, Chang and Tung (2008) integrated the Davis's model by adding DOI's compatibility to it, which has been proven to have a direct effect on perceived usefulness and behavioral intention to use (Wu et al., 2005). At the same time, they excluded trialability and observability, basing this choice on the fact that previous research has not shown correlation between these constructs and information technology.

Lee, Hsieh and Hsu's study (2011) is another example of the integration of TAM and DOI which confirmed that this combination can offer better overall results. Indeed, they explored the relationships among the five attributes of innovations with perceived ease of use and perceived usefulness, and willingness to use and the relation between usefulness with workers' intention to use e-learning systems. Results showed that relative advantage, compatibility, complexity, trialability, and observability had a major impact on the workers' behavioral intention of using e-learning systems. Moreover, their research confirmed previous literature revealing that compatibility and relative advantages had positive impact on PU. On the other hand, they found, in contrast to earlier studies, that complexity had a positive impact on PU. Finally, still in contrast to previous research, observability was found to have no impact on PU, while trialability had a negative effect on PU. When exploring the impact that the five attributes of innovations have on PEOU, Lee, Hsieh and Hsu found that complexity impacted it negatively, compatibility and observability had no major impact on it, while relative advantage and trialability were positive related to it.

4 Emotions and Music Consumption

4.1 *An Introduction to Emotions*

Even though the term “emotion” is used frequently in our day-to-day lives, there is still no agreement in the scientific community on a definition (Cabanac, 2002). Indeed, in 1981, the number of definitions proposed by researchers had already reached a point where counting them seemed futile; however, the task was carried out by Kleinginna and Kleinginna (1981), in an attempt to resolve the confusion on the matter, and they gathered 102 definitions.

Acknowledging this problem, Cabanac (2002) propose that “emotion is any mental experience with high intensity and high hedonic content (pleasure/displeasure)”. In the same article, he found large consensus for the multidimensional nature of emotion, comprising subjective experiences of valence and arousal, physiological responses, and behavioral expressions (Canabac, 2002; Ngombe et al., 2022).

We can further expand this definition, as many researchers also believe that emotions are usually short-lived, context-specific, and occupy the foreground of consciousness (Fredrickson et al., 2008). This means that emotions are directed, in some sense, to “objects”. For example, we are sad “about” the death of someone dear to us, or angry “about” something (Aquila, 1974; Juslin et al., 2008).

With respect to the multidimensional nature of emotions, Russell’s (1980) circumplex model of affect proposes that emotions are best represented as a circle in a two-dimensional bipolar space: valence (a pleasure-displeasure continuum) and arousal, or alertness. Consequently, all emotions may be thought of as a linear combination, or as variable degrees of these two dimensions (Posner et al., 2008).

Another major perspective claims that the basic elements of emotions are discrete entities (Harmon-Jones et al., 2017). For example, Ekman and Friesen (1971) proposed a list of basic emotions based on cross-cultural studies on emotion processing in facial expressions. They found that specific facial behaviors are universally associated with particular emotions: happiness, sadness, anger, fear, surprise, disgust, interest.

Starting from Ekman’s research, Plutchik (2001) expanded it using the psychoevolutionary theory, which assumes there are eight basic emotion dimensions arranged in four pairs: joy vs. sorrow, anger vs. fear, acceptance vs. disgust, and surprise vs. expectancy. This model, called “Wheel of Emotions”, was proposed in 1958 and further expanded over the years to describe more complex emotions: those resulting from the combination of two or more basic emotions. This circumplex modeling is depicted in Figure 8.

As proven by this brief introduction, the scientific literature and research on emotions is vast and includes many different theories and definitions. Nonetheless, the models and theories discussed above give us a basic understanding on the topic, allowing us to further explore the relationship between emotions and music consumption in the following sections of this chapter.

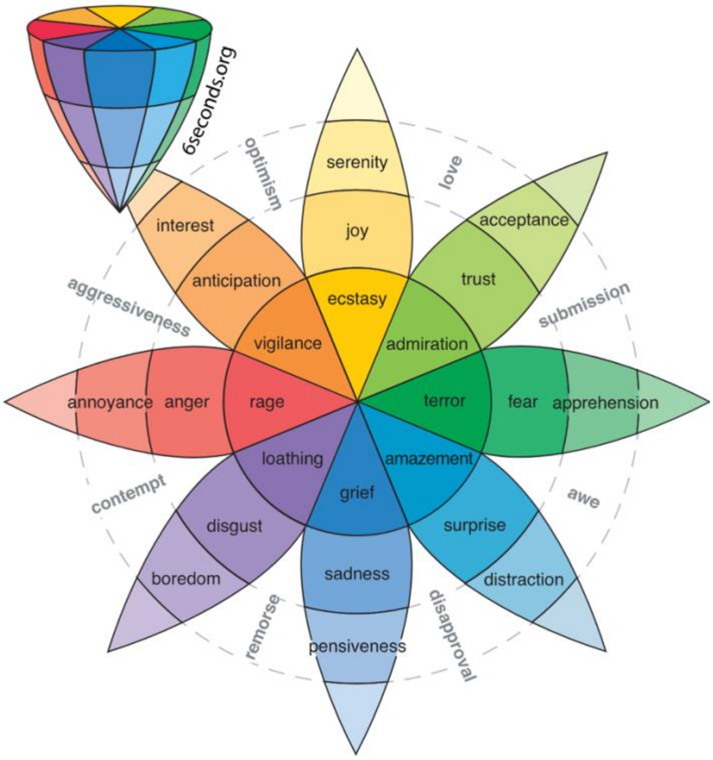

Figure 8. *Plutchik's Wheel of Emotions (Source: 6seconds.org)*

4.2 *Music and Emotions*

Listening to music is a universally pleasurable activity for human beings, and one of its main purposes is the emotional experience it provides (Mori, 2022). People listen to music to regulate their emotions, express emotions, match their current mood, reduce stress and anxiety, or to enjoy themselves (Juslin et al., 2008).

However, research is somewhat divided on whether music can induce emotions or not. Indeed, some scholars, arguing that emotions are aroused when an object is considered to be able to affect an individual's goals, have theorized that music cannot induce emotions at all. While others have argued that it may induce "more subtle, music-specific emotions" (Juslin et al., 2008). However, Juslin and Västfjäll (2008), in their study of emotional reactions to music, challenge these perspectives, positing that music can elicit a range of emotions in listeners, from basic to complex. They propose a theoretical framework detailing the psychological mechanisms contributing to emotions evoked by music:

1. Brain stem reflexes: a process in which music triggers an emotion because one or more fundamental acoustical properties of the music are interpreted by the brain stem as signaling a potential and critical situation.
2. Evaluative conditioning: a process in which a piece of music triggers an emotion merely by being frequently combined with other positive or negative stimuli.
3. Emotional contagion: a process in which an emotion is triggered by music because the individual feels the emotional expression of the music and then “mimics” it internally, leading to the activation of the same emotion, either through muscle feedback or direct stimulation of the corresponding emotional representations in the brain.
4. Visual imagery: a process in which an individual is induced to feel an emotion because he or she makes up visual ideas while listening to music. The feelings felt are the consequence of the music and pictures interacting closely.
5. Episodic memory: a process in which an emotion is triggered in an individual as the music recalls a specific event in the listener’s past.
6. Musical expectancy: a process in which an emotion is triggered in an individual when a certain feature of the music contradicts, delays, or confirms his or her expectations on how the piece of music will continue.

Juslin and Västfjäll’s (2008) framework makes up for only a little portion of the many parameters that are a function of the musical trigger of emotions. Other parameters include: mood, physiological state, cultural background, and preferences of the listener; the performance style; the musical style; and the composer's arrangement of musical features (Schubert, 2004).

Schubert (2004) argues musical structure, or more specifically, combinations of musical features may account for a significant portion of emotions in music. Musical structure refers to a variety of characteristics of a piece of music including tempo, loudness, pitch, intervals, mode, melody, rhythm, harmony, and various formal aspects (Gabrielsson, 2014).

Because a typical musical composition comprises complex combinations of features, determining which musical characteristic (or combination of them) is contributing to the perceived emotion has proven to be a difficult task (Schubert, 2004). However, many studies have been carried out to investigate this problem. For instance, in 2002, Husain, Thompson, and Schellenberg set to explore the effects of musical tempo and mode on arousal and mood. After presenting participants with one of four renditions of a Mozart’s sonata, he found that manipulations in music were related to changes in arousal and mood. In particular, fast tempo increased listeners’ levels of arousal, while slow tempo brought decreases in arousal. At the same time, major mode caused positive shifts in mood, while minor mode induced negative mood shifts.

Another study carried out by Schubert (2004) found that shifts in loudness and tempo were related to increases in arousal, with loudness being the most dominant.

Concluding, the relationship between music and emotions is a complex and multifaceted one, as demonstrated by the vast amount of research on the topic. We have only given a brief overview of the overall topic to understand how different factors combine to trigger emotions in listeners.

4.3 *Uses and Gratification Theory: Focus on Music Consumption*

The Uses and Gratification Theory explains how and why people use media to satisfy their needs and desires, and music is no exception.

According to general consensus, Uses and Gratification Theory is a branch of media effects research that focuses on the gratifications that draw and keep audiences interested in various media and content. Early U&G research tended to be descriptive in nature and attempted to group audience reactions into useful categories. Then, during the 1950s and 1960s, U&G researchers began to explore the social and psychological factors that influence media use (Ruggiero, 2000).

Later, in 1973-74, Katz, Blumer, and Gurevitch started researching how people saw the mass media. In their study, they provide a framework for understanding the correlation between media and audiences:

1. The audience is seen as proactive and goal-directed in their use of mass media.
2. The audience takes significant initiative in aligning their needs with their choice of media.
3. The media face competition from alternative sources of need satisfaction.
4. The objectives behind mass media usage can often be inferred from the information provided by the audience members themselves.
5. Judgments about the cultural importance of mass communication should be put on hold while examining audience perspectives in their context.

Moreover, the motivations for media use were grouped in terms of: diversion (e.g., as an escape from routine or for emotional release); social utility (e.g., to gather information for conversations); personal identity (e.g., to reaffirm attitudes, beliefs, and values); and surveillance (e.g., learning about one’s community, events, etc.).

The research conducted by Katz and his colleagues supplied the theoretical groundwork for the building of the Uses and Gratifications approach. The study of this topic has since been deepened and expanded to investigate the different types of media. Indeed, the U&G approach has been applied to music consumption research, providing valuable insights into the motives that bring individuals to listening to music. For example, Lonsdale and North (2011), basing their work on McQuail et al.'s (1972) model of media gratifications, which adds mood management as a motivation for media usage, identified six main reasons why participants to their study listen to music: positive mood management, diversion, negative mood management, interpersonal relationships, personal identity, and surveillance. Their results show that users typically listen to music to control or regulate their moods as well as a diversion to get away from daily boredom or to pass the time. On the other hand, personal identity and interpersonal relationships were of secondary importance, while surveillance was discovered to be the least significant of the six reasons why audiences listen to music.

In addition, several of the motivations for media use have been further investigated by scholars. Saarikallio and Erkkilä (2007) have studied the role of music in regulating adolescents' mood. Their findings show that music is a versatile mood-regulating tool, since it provided teenagers with tools for increasing and regaining well-being, as well as making their emotional lives more diverse. Moreover, they identified seven distinct regulatory strategies:

- Entertainment: in this case music is usually in the background and is used for uplifting spirits and maintaining a positive mood.
- Revival: it involves mainly listening, but also every other activity such as singing, playing, and writing music. In this case, music provides experiences that were both relaxing and energizing.
- Strong sensation: it involves any kind of musical activity in which the adolescent is highly invested. In this instance, individuals appeared to search for intense emotional experiences from music in order to achieve strong enjoyment, excitement, and pleasure.
- Diversion: it involves listening, singing, and playing cheerful and pleasant music in order to forget about undesired states of mind.
- Discharge: it involves listening or playing music that is aggressive or sad, which gives form to negative emotions. In this way, adolescents expressed and released their negative feelings such as anger, sadness, and depression.

- Mental work: it involves listening or writing songs alone. Here, music encourages and facilitates mental imagery, contemplation, and daydreaming as well as reflection on the emotions felt in the moment.
- Solace: it involves paying attention to the lyrics of a piece of music, as individuals identify with them. Here, music offers comfort in times of need.

Hargreaves and North (1999), on the other hand, investigated the social functions of music in everyday life. They found that there are three main ways through which the social functions of music manifest:

- Self-identity management: music can help shape an individual's self-identity by allowing them to express themselves and identify with certain social communities and subcultures.
- Interpersonal relationships management: music plays a significant role in shaping interpersonal relationship as it can help influence how individuals perceive and respond to other. For example, in musical preference evaluations, conformity and prestige effects show a desire for acceptability into a specific social group.
- Mood management: music can significantly contribute to mood management by giving people a way to control their emotional states and by influencing how they react to their surroundings. Indeed, musical tastes reflect situationally-determined and specific-goals.

Finally, Chamorro-Premuzic and Furnham (2007) have investigated whether personality traits can explain how people use music in everyday life. Their study highlights that people listen to music for a variety of reasons, which might be connected to distinct personality traits and cognitive skills. Moreover, the results suggest these reasons can be grouped into three different categories:

- Rational/cognitive appreciation: this describes listeners who focus on comprehending, analyzing, or critically evaluating the structure and lyrics of the music they are listening to. TIE (Typical Intellectual Engagement) scores are higher in those who connect with music in this way, reflecting a more open and intellectual disposition. Furthermore, these individuals typically have higher IQ scores.
- Emotional regulation: some individuals use music as a primary tool to control, alter, or boost their emotions. According to this study, those who utilize music for this reason are more likely to have introverted, neurotic, or unconscientious personality traits. In this sense, music may be a means of mood regulation, such as listening to sad music

when sad. This can be helpful especially for individuals with higher neuroticism as they tend to be emotionally unstable and experience emotions more intensely, especially the negative ones, such as anxiety and depression.

- Background to other activities: here music is used as an accompaniment to other activities, such as studying, social events, or working. Listeners usually have low distractibility levels.

In closing, the Uses and Gratification theory has offered a useful framework for understanding the diverse motives underlying music consumption. Researchers have identified multiple reasons why people listen to music, including cognitive appreciation, emotional regulation, background to other activities, mood management, interpersonal relationships, personal identity, and surveillance. As a result, music has a profound psychological and emotional effect on listeners. This is demonstrated by the versatility of music as a tool for mood regulation, its social roles in daily life, and its ability to alter self-identity and interpersonal connections.

4.4 *The Role of Positive and Negative Emotions in Music Consumption*

We can further deepen the research investigating the people's reasons for listening to music by dividing emotions in positive and negative.

Positive emotions are indicators of an individual's overall well-being or happiness; they involve pleasant or desirable situational responses, spanning from interest and satisfaction to love and joy. They typically occur in safe or controlled situations, unlike negative emotions, which are adopted to provide a quick response to a threat (Cohn et al., 2009). Consequently, negative emotions function to shield us from potentially harmful circumstances (Garrido et al., 2011). Negative emotions are then defined as "unpleasant or unhappy emotions which are evoked in individuals to express a negative affect towards an event or person" (Pam, 2013).

Solomon and Stone (2002) provide a summary list of both positive and negative emotions in their study, which we report below (Table 1).

According to research, music may induce or potentially control positive and negative emotions. In 2019, Cook, Roy and Welker found that upbeat and rhythmic music is used boost positive emotions, suppress negative emotions, and increase arousal. Results from the same study also tend to suggest that people may consume diverse music for different emotion regulation strategies.

These strategies are further investigated by a study conducted by Saarikallio (2011). He found that music is mainly used as a mood booster, a diversion, or to relax. Additionally, listening to music that conveys one's feelings can be a way to release and vent anger or sadness. Similarly to a comforting friend, music may offer solace, but also it may be used to "psych up" oneself, uplifting mood, and increase energy levels for an activity.

Table 1*. Positive and negative emotions (Source: Solomon et al., 2002)*

Positive	*Negative*
Good	Bad
Pleasure	Pain
Happy	Sad
Right	Wrong
Virtue	Vice
Approach	Avoidance
Approval	Disapproval
Innervating	Enervating
Healthy	Unhealthy
Calm, comfort	"Upset"
Conducive to happiness	Conducive to unhappiness
Positive attitude to object	Negative attitude to object
Positive attitude to self	Negative attitude to self
Positive attitude to relationship	Negative attitude to relationship
High status (object)	Low status (object)
High status (self)	Low status (self)
Responsibility (praise other)	Responsibility (blame other)
Responsibility (praise self)	Responsibility (blame self)

While investigating the reasons for personal music listening, Randall and Rickard (2017) found that emotional reasons for listening to music were reported more frequently when the individual was in a negative mood. This suggests, contrary to the notion that emotional reasons are the most important factor when listening to music, that it depends on the initial emotional state. Moreover, the study discovered that background music was the most common reason for listening to music, and passive listening was more frequent – apart from situations in which the listener was in a negative mood – than active listening. This, Richard and Rickard explained, is consistent with other studies showing that listening to music is largely a solitary and self-regulatory activity that allows individuals to choose music that suits their particular mood and situation.

Regarding the use of music as an emotional self-regulating tool, Chin and Rickard (2013) found that consuming music to regulate emotions seems to be consistently more effective for one's well-being than listening to music to repress emotions. Their results also show that increasing the amount of music consumption, if done with the purpose of suppressing emotions and thoughts, may lead to undesirable outcomes for one's well-being.

In conclusion, research on music consumption indicates that people listen to music for a variety of reasons, with emotional self-regulation playing a big role. The motivations and frequency of music listening are greatly influenced by both positive and negative emotions, with negative feelings frequently resulting in more active and emotionally charged listening experiences. On the other hand, passive listening is more common in neutral or positive moods. Finally, studies also show that while using music to repress emotions might have negative consequences, utilizing it to regulate emotions improves one's wellbeing.

5 Scientific Paper

5.1 *Hypotheses Development*

The purpose of this chapter is to provide readers with a deeper, more insightful comprehension of the various variables that have been meticulously selected for the Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis. To achieve this, in the previous chapters we have conducted an extensive examination of the existing literature, drawing from a diverse range of scholarly sources to not only contextualize these variables within the wider research landscape, but also to highlight their significance and relevance to our study. Now, we will use those findings to develop the hypotheses of this study.

5.1.1 Positive and negative emotions

The connection between music and emotions is intricate and multi-dimensional, as evidenced by the extensive body of research dedicated to exploring this subject. Accordingly, we used the Uses and Gratification theory to understand how and why people use media to satisfy a wide array of needs and desires that they experience. The theory, developed by Katz, Blumer, and Gurevitch between 1973 and 1974, provides a framework that highlights the active and goal-driven nature of the audience in their consumption of media. It suggests that the audience plays a significant role in how their needs are met by the media of their choice. Moreover, it acknowledges that media face competition from other sources in the quest of satisfying the audience’s needs. The framework also proposes that individual audience members provide themselves data that may be used to infer many of the objectives of media consumption.

The U&G theory, then, identifies motivations for media use such as diversion, social utility, personal identity, and surveillance (Katz et al., 1973). Within the context of music consumption, research has found six main reasons for listening to music: positive mood management, diversion, negative mood management, interpersonal relationships, personal identity, and surveillance (Lonsdale et al., 2011; Hargreaves et al., 1999; Chamorro-Premuzic et al., 2007).

When examining the impact of positive and negative emotions on music consumption, research demonstrates that music may either trigger or regulate these emotions. This complex relationship with emotions allows music to fulfill a variety of purposes in listeners' lives, such as boosting moods, diversion, relaxation, emotional release, comfort, and improving energy levels. The motivations for listening to music and the amount of music listened are greatly influenced by both positive and negative emotions, with negative feelings frequently resulting in more active and emotionally charged listening experiences. On the other hand, passive listening is more common in situations characterized by neutral or positive moods (Saarikallio, 2011; Cook et al., 2019; Randall et al., 2017; Chin et al., 2013).

Moreover, with respect to music streaming services, Kinally and Bolduc (2020) integrated the Theory of Planned Behavior and Uses and Gratification to comprehend music streaming intentions and behavior. Their findings show that the entertainment/mood management and social interaction motives significantly predicted music streaming intentions. Moreover, in predicting the duration of time devoted to music streaming services, the TPB attitudes and social interaction motivation were significant predictors, and the addition of motive components substantially improved the predictive power. This shows that while concentrating on behavior, adding U&G motives was very beneficial.

The aforesaid discussion of the previous literature, then, lends to support the following hypothesis:

H_1: Negative Emotions have a positive and significant impact on users' Diverse Music Consumption.

H_2: Positive Emotions have a positive and significant impact on users' Diverse Music Consumption.

5.1.2 Moderating effects of the Technology Acceptance Model

The Technology Acceptance Model (TAM) is an information systems theory that examines the factors influencing people's decision to adopt and use technology. Created by Fred Davis in 1986, the model is based on the Theory of Reasoned Action (TRA), which was developed by Fishbein and Ajzen in 1975. Since its introduction, the TAM has come to be among the most popular and significant theories for predicting and explaining technology acceptance and adoption.

The TRA is a framework that aims at understanding how beliefs, attitudes, intentions, and behavior are related to one another. According to the TRA, two important variables influence a person's intentions: their attitude towards the behavior and their subjective norm, which is made up of normative beliefs and the motivation to stick to them (Fishbein et al., 1975).

Using the TRA as its foundation, the TAM focuses on understanding users' acceptance of technology. It argues that a person's intention to use a technology, which ultimately predicts their actual use of it, is determined by two main factors: perceived usefulness (PU) and perceived ease of use (PEOU). PU refers to the extent to which an individual believes that adopting a specific technology will improve their task performance. On the other hand, PEOU considers the extent to which an individual believes that using a specific technology won't require much effort. Moreover, perceived ease of use can also indirectly influence the perceived usefulness because when a system is easy to use, it tends to seem more helpful since users can focus on their tasks instead of navigating complicated technology (Davis, 1986).

Various studies have used the TAM to assess user acceptability in recommender systems for a variety of goals. For example, Armentano, Christensen, and Schiaffino (2015) applied the model to assess user acceptance of recommender systems in the movies domain. Their findings show that perceived usefulness is a critical contributor in users' acceptance of a new recommender system. On the other hand, perceived ease of use did not appear to be as important in the adoption of a new system. Yet, it did appear to have a great impact in determining perceived usefulness itself.

Similar conclusions were also reached by Hu and Pu (2009), who evaluated a personality-based recommender system for movies using the Technology Acceptance Model. Their results confirm that perceived accuracy plays a dominant role in determining user acceptance of a recommender system, while perceived ease of use shows a substantial correlation with users' acceptance intents and perceived accuracy.

Thus, considering the results of previous studies, we formulate the following hypotheses:

H_3: Perceived Usefulness of recommender systems in music streaming services moderates the relationship between Negative Emotions and Diverse Music Consumption.

H_4: Perceived Usefulness of recommender systems in music streaming services moderates the relationship between Positive Emotions and Diverse Music Consumption.

H_5: Perceived Ease of Use of recommender systems in music streaming services moderates the relationship between Negative Emotions and Diverse Music Consumption.

H_6: Perceived Ease of Use of recommender systems in music streaming services moderates the relationship between Positive Emotions and Diverse Music Consumption.

Finally, Figure 9 effectively illustrates the comprehensive conceptual framework that has been brought to light through our thorough examination of the existing literature. This visual representation serves as a synthesis of the various theoretical perspectives, hypotheses, and relationships we have identified and explored, thereby providing readers with a clear and coherent understanding of the key elements supporting our research inquiry.

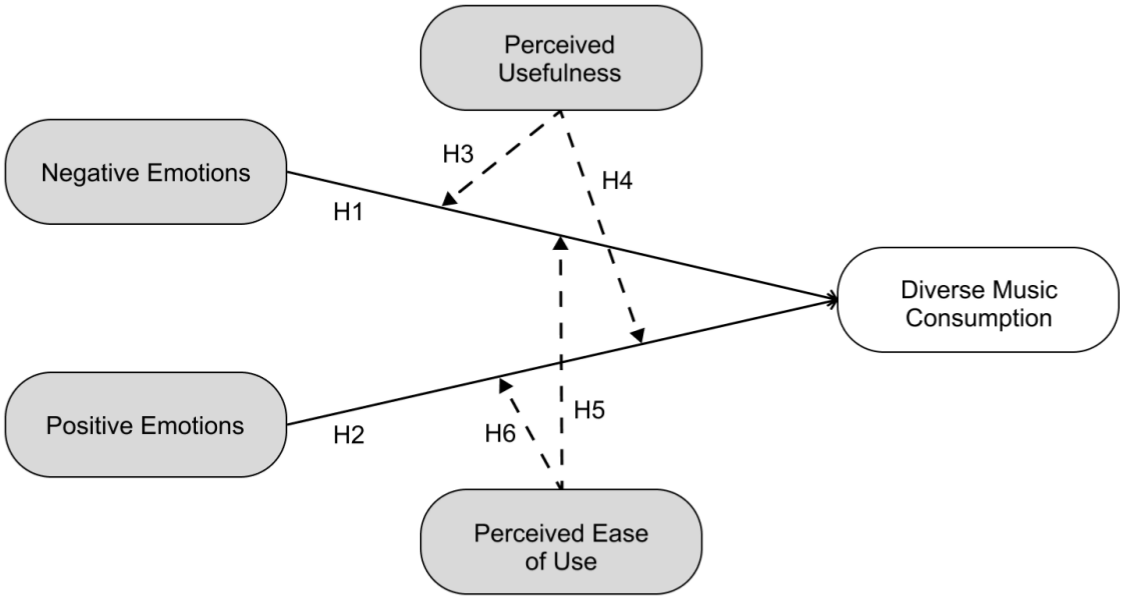

***Figure 9**. Researcher framework*

5.2 *Research Methodology*

5.2.1 Research instrument

The questionnaire for the study, prepared on Qualtrics XM, was divided into four broad sections. The first section asked respondents their demographic characteristics. The second section sought information on the users' preferred music medium, whether they were premium subscribers of a music streaming service or not, and their frequency of music consumption. In addition, it included statements related to the independent variable of Diverse Music Consumption (DMC). The third section included statements related to the moderation variables of Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of recommender systems in music streaming services. While the last section included statements for the two dependent variable of Negative Emotions (NE) and Positive Emotions (PE). A 5-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree) were used to assess these items. Table 2 provides the number of items making up each variable along with their source.

Table 2. *Measures*

Variable	No. of Items	Source
Diverse Music Consumption (DMC)	3	Madnani et al. (2020)
Perceived Ease of Use (PEOU)	4	Pu et al. (2011); Jones et al. (2009); Armentano et al. (2015)
Perceived Usefulness (PU)	7	Pu et al. (2011); Jones et al. (2009); Armentano et al. (2015)
Negative Emotions (NE)	4	Sarafim-Silva et al. (2019); Tarrant et al. (2000)
Positive Emotions (PE)	5	Sarafim-Silva et al. (2019); Tarrant et al. (2000)

The appropriateness of the factor analysis for these items was assessed using the Kaiser/Meyer/Olkin (KMO) test and Bartlett's test of sphericity. The KMO test, which provided a measure of sampling adequacy, yielded a result of 0.868, exceeding the required value of 0.50. Furthermore, Bartlett's test reinforced the suitability of the factor analysis, which was 2670.391, significance at $p < 0.000$. Bartlett's test suggests that the item correlation matrix is not an identity matrix, which allows us to proceed with the analysis.

In the course of the exploratory factor analysis, items that did not sufficiently load on a specific factor (<0.40) or had cross loadings were expected to be removed. However, as all items had loadings exceeding 0.40, no deletions were necessary.

5.2.2 Sample design and data collection

An online questionnaire was floated on social medias to collect primary responses for the study, in particular on WhatsApp groups, LinkedIn, and Reddit. To improve the response rate and encourage greater participation, participants were assured of anonymity of responses. This was also done to encourage respondents to answer as honestly as possible.

Due to the absence of a sample framework or list of such customers, we opted for a convenience sampling method. According to IFPI's 2022 Engaging with Music report, the use of subscription audio streaming was highest in younger age groups: 54% of people in the age group of 16-24 years are subscribed to a music streaming service, as well as 56% of people in the age group of 25-34. These percentages are decreasing in older age groups. Since the highest number of social media users also belongs to these age groups: 12% of total social media users are between 13 and 19 years, 31% are between 20 and 29 years, and 22.2% are between 30 and 39 years (We Are Social, 2023), it was considered appropriate to use digital/social media platforms to connect with possible users of music streaming services.

A total of 242 responses were collected and included at the final data set. According to Israel (1992), this sample size meets the necessary condition of required sample size i.e., 204 respondents considering a 95% confidence level, standard deviation of 0.5 and ±7% precision level, with a population larger than 100,000. A standard deviation of 0.5 reflects the highest variability within a population, while a confidence level of 95% means that 95 out of 100 samples will contain the true population value within the ±7% precision range. However, one must bear in mind that there is always the possibility that sample obtained does not represent the true population value.

Another strategy, indicated by Israel (1992), for determining the sample size is to mirror the sample size of studies similar that are similar to the one planned. In this case, we looked at Gupta and Singharia's (2021) study on the consumption of OTT media streaming in COVID-19 lockdown, where they used a data set made of 182 responses.

Finally, Comrey (1988) regarded a sample size of 200 as reasonably satisfactory for factor-analytic work with 40 or fewer variables. Therefore, our sample of 242 should be more than adequate to successfully carry out our analysis.

Table 3 provides the demographic profile of respondents.

5.2.3 Data analysis

Although self-administered surveys are one of the most frequently utilized techniques in the social sciences, they also introduce the risk of common method variance and bias. Common method bias can appear when both the independent and dependent variable is captured by the same person. These factors can potentially compromise the reliability and accuracy of the empirical findings (Kock et al., 2021).

Consequently, we used different methods to verify that our study is free from method bias. Results from the principal component analysis (PCA) revealed that the 23 items could be placed into five categories with eigenvalues greater than 1: 6.362, 4.031, 1.910, 1.290, and 1,102. The five-factor solution accounted for 63.41% of the variance. The first factor explains the 27.66% of the total variance; thus, indicating method bias is not a serious issue in this study. Moreover, Table 5 shows that the inter-correlations display no value equal or above 0.9, with the highest inter-correlation at only 0.693. These results further confirm that our study does not suffer from method bias.

***Table 3**. Respondents' profile*

Characteristic	Frequency	Percent (%)
Gender		
Male	143	59.09%
Female	95	39.26%
Non-binary/Third gender	3	1.24%
Prefer not to say	1	0.41%
Age group		
Under 18	6	2.48%
18-24	123	50.83%
25-34	54	22.31%
35-44	25	10.33%
45-54	18	7.44%
55-64	6	2.48%
65-74	9	3.72%
75 or older	1	0.41%
Education		
Less than high school	8	3.31%
High school graduate	69	28.51%
Associate degree	9	3.72%
Bachelor's degree	92	38.02%
Master's degree	44	18.18%
Professional degree	9	3.72%
Doctorate	5	2.07%
Other	6	2.48%
Country of residence		
Europe	175	72.31%
North America	50	20.66%
South America	8	3.31%
Africa	3	1.24%
Asia	3	1.24%
Oceania	3	1.24%
Music medium		
Streaming app (e.g., Spotify, Apple Music)	228	94.21%
Local music stored on phone	25	10.33%
Radio	41	16.94%
CDs, cassettes, or vinyl	37	15.29%
Other	10	4.13%
Premium member of streaming services		
Yes	189	78.10%
No	53	21.90%
Average of daily music listening (hrs)		
<1	48	19.83%
1-2	87	35.95%
2-3	44	18.18%
3-4	31	12.81%
4+	32	13.22%

Table 4. *Validity and reliability for constructs*

Constructs	Items	Loadings	AVE	CR
Diverse Music Consumption	I keep track of new music that I come across (e.g., new artists or recordings)	0.792	0.598	0.816
	I am intrigued by musical styles that I am not familiar with and want to find out more	0.703		
	I often read or search the internet for things related to music	0.819		
PEOU	I became familiar with the recommender system very quickly	0.789	0.665	0.887
	I find the recommender system easy to use	0.888		
	My interaction with the recommender system is clear and easy to understand	0.871		
	I easily find the recommended songs	0.702		
PU	I found the recommended songs attractive	0.892	0.658	0.931
	Using the recommender to find what I like is easy	0.814		
	The recommended songs are tailored to my taste	0.821		
	The recommender gives me good suggestions	0.856		
	The system understands my preferences regarding music	0.789		
	The technology used by the recommender system is accurate	0.711		
	In general, I am satisfied with the recommended songs	0.782		
Negative Emotions	It helps me through difficult times	0.845	0.632	0.873
	It relaxes me when I am stressed/anxious	0.797		
	It reduces loneliness	0.779		
	It relieves boredom	0.758		
Positive Emotions	It helps me being creative/using my imagination	0.767	0.547	0.821
	It helps me express my feelings/emotions	0.746		
	It facilitates thinking	0.721		
	It helps me maintaining a good mood	0.632		
	I enjoy the music	0.581		

Table 5. *Discriminant validity*

Constructs	DMC	NF	PEOU	PU	PF
Diverse Music Consumption	**0.773**				
Negative Emotions	0.441	**0.795**			
PEOU	0.222	0.122	**0.816**		
PU	0.144	0.122	0.427	**0.811**	
Positive Emotions	0.506	0.638	0.176	0.186	**0.693**

First, we employed SPSS version 26.0 for carrying out the descriptive statistics and reliability analysis on the gathered data, as well as for evaluating the demographic characteristics of the sample and the internal consistency of the constructs. Following this, the research model was analyzed using Partial Least Squares (PLS) analysis with the assistance of SmartPLS 3.0 software.

For this study, a Partial Least Squares-based structural equation modeling (SEM) was employed to model and estimate intricate relationships among several dependent and independent variables, also referred to as PLS path modeling. PLS-SEM analysis is advantageous when used with small sample sizes, as it is in our case (Hair et al., 2014).

There are two components to a PLS path model. The constructs are connected first by a structural model, also called inner model. The relationships between the constructs are also shown in the structural model. Then, there are the measurement models of the constructs (also called outer models), which show the connections between the constructs and the indicator variables (Hair et al., 2021).

Finally, to validate the significance of the path coefficients and the loadings, we employed a bootstrapping method (5000 resamples). Bootstrapping is a method of resampling that extracts numerous subsamples from the original data (with replacement) and develops models for each of these subsets. Consequently, researchers get a substantial number of model estimates, usually 5,000 or more, that can be used to calculate the standard error for each parameter of the model (Hair et al., 2014).

5.3 *Findings and Results*

5.3.1 Measurement model

Initially, the measurement model was evaluated for its convergent validity. The assessment was conducted using factor loadings, Composite Reliability (CR), and Average Variance Extracted (AVE) as the evaluative criteria. Table 4 shows that all item loadings exceeded the recommended value of 0.5. Factor loading is the correlation between an item and the factor (Tavakol et al., 2020), and correlation loadings are considered minimal if above 0.3, important if above 0.4, and practically if above 0.5 (Taherdoost et al., 2014). Composite reliability values, representing the extent to which the construct indicators reflect the underlying latent construct, are almost all in the range between 0.7 and 0.9, which translates to “satisfactory to good”. Only one value exceeds this range – PU is equal to 0.931 – but it is still below 0.95, over which values are considered problematic as their high value may indicate their redundancy. Finally, average variance extracted (AVE) values are all above the recommended value of 0.5, which indicates that the construct explains 50% or more of the indicators' variance that make it up (Hair et al., 2021).

The reliability of our construct can also be evaluated through Cronbach's alpha (α). We found that our Cronbach's alpha values are all above the recommended value of 0.7 and none are above 0.95. However, Hair, Howard, and Nitzl (2020) argue that Composite Reliability, a weighted measure, is more precise than α.

Subsequently, we inspect the discriminant validity, this parameter quantifies the degree to which a construct is distinguishable from other constructs within the structural model based on empirical evidence. One method, proposed by Fornell and Lacker in 1981, argues that shared variance between all model constructs should not be larger than their AVEs. Table 5 illustrates that the square root of the AVE (diagonal values) of each construct is larger than its corresponding correlation coefficients indicating adequate discriminant validity (Hair et al., 2021). Further research, however, has theorized that this method is not suitable for assessing discriminant validity. Thus, today the heterotrait–monotrait ratio (HTMT) of correlations is considered a better alternative when assessing discriminant validity. Consequently, we used this new method for determining discriminant validity, and results are shown in Table 6. A threshold value of 0.85 is suggested when working with constructs that are conceptually different (Hair et al., 2021). As shown in Table 6, all our results are below the value recommended.

Table 6. *Heterotrait-monotrait (HTMT)*

Constructs	DMC	NF	PEOU	PU	PF
Diverse Music Consumption					
Negative Emotions	0.541				
PEOU	0.283	0.144			
PU	0.158	0.156	0.529		
Positive Emotions	0.713	0.829	0.229	0.236	

5.3.2 Structural model

After confirming the reliability and validity of the outer models, there are numerous steps that must be taken to assess the hypothesized relationships within the inner model. We followed Ali, Kim, and Ryu (2016) and looked at the R^2, beta (β), and corresponding t-values via a bootstrapping procedure with a resample of 5,000. We also checked the predictive relevance

(Q^2) and the effect sizes (f^2). R^2 measures the variance explained in each of the endogenous constructs and is, therefore, a measure of the model's explanatory power (Hair et al., 2021).

We started by looking at the relationships between the variables. Negative emotions positively and significantly affected diverse music consumption ($\beta = 0.745$, $p<0.1$), and so do positive emotions ($\beta = 0.798$, $p<0.05$). Thus, both H1 and H2 are supported (see Table 7). Moreover, negative and positive emotions explain 33.4% of variance in diverse music consumption (R^2=0.334). Acceptable R^2 values depend on the context. For example, according to Hair, Sarstedt, and Ringle (2021) R^2 values of 0.75, 0.50, and 0.25 can be considered substantial, moderate, and weak. On the other hand, Ferguson (2009) indicates values above 0.25 as being moderate. Finally, Cohen (1988) suggests that values over 0.26 indicate a substantial model.

Then, we looked at effect sizes (f^2), which provides an estimation of the predictive ability of each independent construct in the model (Hair et al., 2020). The p-value indicates the singificance of the relationships, but it doesn't illustrate the magnitude of the effect. As a result, understanding data and outcomes can be challenging for readers. Thus, it's crucial to report both the substantive significance (f^2) and the statistical significance (p) (Ali et al., 2016). According to Cohen (1988), values above 0.02 and up to 0.15 are considered small; those between 0.15 and 0.35 are medium; and, finally, those above 0.35 are large effects. In our case, values are small.

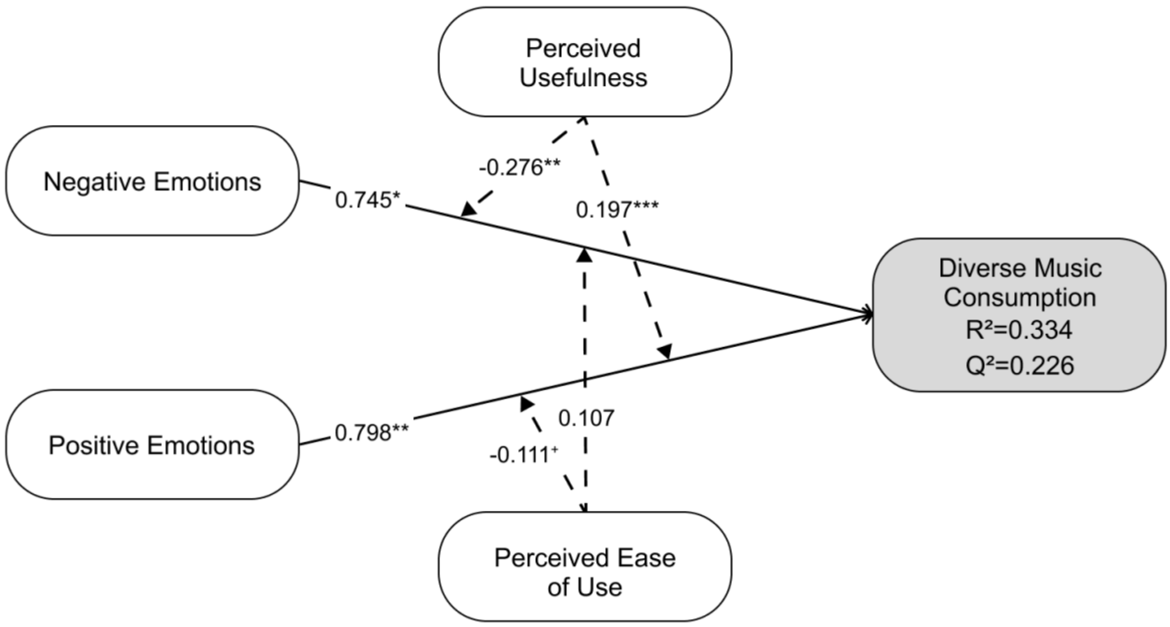

Figure 10. *Structural model*

A third measure used to evaluate prediction is the Q^2 value, which is also known as blindfolding. When analyzing Q^2, values greater than zero have significance, while values less than zero suggest an absence of predictive importance (Hair et al., 2020). Figure 10 shows that our variable has acceptable predictive relevance, as $Q^2 = 0.226$.

Table 7. *Structural estimates (hypotheses testing)*

Hypotheses	Beta	t-value	f^2	p-value	Decision
H1: Negative Emotions→DMC	0.745	1.800*	0.017	0.036	Supported
H2: Positive Emotions→DMC	0.798	2.639**	0.033	0.004	Supported
H3: PU×Negative→DMC	-0.276	2.595**	0.063	0.005	Supported
H4: PU×Positive→DMC	0.197	2.393**	0.038	0.009	Supported
H5: PEOU×Negative→DMC	0.107	1.068	0.006	0.143	Not Supported
H6: PEOU×Positive→DMC	-0.111	1.444^{+}	0.009	0.075	Supported
Mod: PEOU→DMC	0.212	0.602	0.002	0.274	Moderator
Mod: PU→DMC	0.997	2.353**	0.058	0.010	Moderator

*Notes: $^{+}p<0.10$; * p<0.05; **p<0.01; ***p<0.00*

5.3.3 Moderation analysis

This study hypothesizes that the factors of the TAM in relation to the recommender systems of music streaming services, specifically Perceived Ease of Use and Perceived Usefulness, would moderate the relationships between Negative Emotions and Diverse Music Consumption and Positive Emotions and Diverse Music Consumption. A moderating effect is triggered by variables that influence the strength or direction of a relationship between an exogenous (independent) and an endogenous (dependent) variable (Henseler et al., 2010). To estimate moderating effects, we used the product term approach. In this approach, we use an additional latent variable in the structural model which represents the product of the independent variable and the moderator variable; thus, getting the following variables: PU×NegativeEmotions, PU×PositiveEmotions, PEOU×NegativeEmotions, and PEOU×PositiveEmotions.

As shown in Table 7, the estimated standardized path coefficients for the effect of the moderators on diverse music consumption were all significant except for H5. This indicates that the Perceived Usefulness moderate both the relationships between Negative Emotions and Diverse Music Consumption and Positive Emotions and Diverse Music Consumption. Perceived Ease of Use, instead, while showing a significant effect in moderating the relationship between Positive Emotions and Diverse Music Consumption, it does not show a significant moderation effect on the relationship between Negative Emotions and Diverse Music Consumption. Thus, H3, H4, and H6 were accepted while H5 was not.

5.4 *Discussion*

This study endeavored to test a model of the effects of positive and negative emotions on the respondents' diverse music consumption. In addition, this research also examined how the main factors of the Technology Acceptance Model – Perceived Usefulness and Perceived Ease of Use – in relation to the recommender systems of music streaming services moderate the effects of emotions on the respondent's diverse music consumption.

Considering the aim and objectives of this study, six hypotheses were tested. The results of the structural equation modelling support all the hypotheses except for one – H5 – so, we conclude that positive and negative emotions do indeed influence listeners' consumption of diverse music. Moreover, the results also confirmed that PEOU and PU of the recommender systems of music streaming services moderate the relationship between positive and negative emotions and listeners' consumption of diverse music; with only PEOU not showing a significant moderation effect on the relationship between negative emotions and diverse music consumption.

Having summarized the key findings of this study, it is now crucial to delve deeper into their meaning and implications. By addressing each result in the context of our research objectives and the current body of literature, we may draw relevant connections, uncover crucial insights, and highlight the distinctive contributions of our work to the field.

Support for our first hypothesis comes from studies indicating that individuals experiencing negative emotional states tend to engage in more active and emotionally charged listening experiences (Randall et al., 2017). In these situations, music consumption may serve several purposes, such as mood regulation, emotional discharge, and solace (Saarikallio et al., 2007; Hargreaves et al., 1999). People who are experiencing negative emotions may seek out diverse music to find what resonates with their feelings or gives them the desired emotional relief. Moreover, negative emotions, such as boredom and frustration, can drive listeners to seek novelty as a form of distraction or escapism (Saarikallio et al., 2007).

Our second hypothesis is supported by the discussion on how music consumption contributes to emotional regulation and provides a background for various activities. People in positive or neutral emotional states may engage in more passive listening experiences, using music to maintain or boost their positive feelings (Chamorro-Premuzic et al., 2007). Diverse music consumption can provide different types of positive experiences, such as relaxation, excitement, or pleasure, depending on the listener's context or preferences. Moreover, positive emotions can foster curiosity and openness to new experiences.

Thus, in both cases, emotions can lead to increased consumption of new and diverse music. Regarding the moderator role of PU and PEOU of recommender systems of music streaming services in the relationship between emotions and diverse music consumption, we have formulated four different hypotheses.

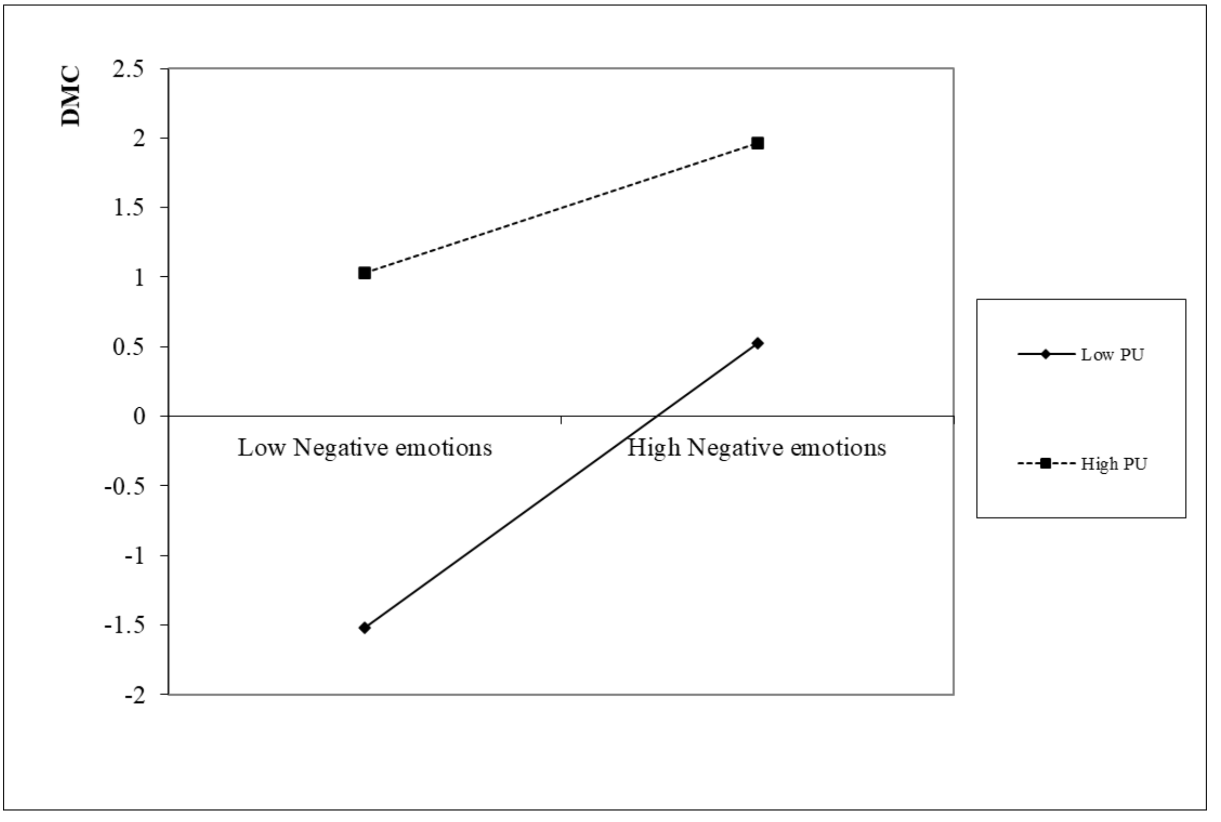

Figure 11. H3: PU×Negative → DMC

Figure 11 helps us understand how PU moderates the relationship between Negative Emotions and Diverse Music Consumption. The plot shows a steeper and positive gradient for low PU as compared to high PU. This shows that the impact of negative emotions in increasing diverse music consumption is stronger when a recommender system is perceived as less useful. Indeed, as previously discussed, users experiencing negative emotions might be more inclined to seek new and diverse music as a means of mood regulation, hoping to find songs that can help them alleviate or express their emotional state. Thus, when users perceive the recommender system as less useful, they may have lower expectations for the music suggestions provided by the platform. This lowered expectation might make them more open to actively exploring new and diverse music, as they may not be as heavily influenced by the platform's recommendations.

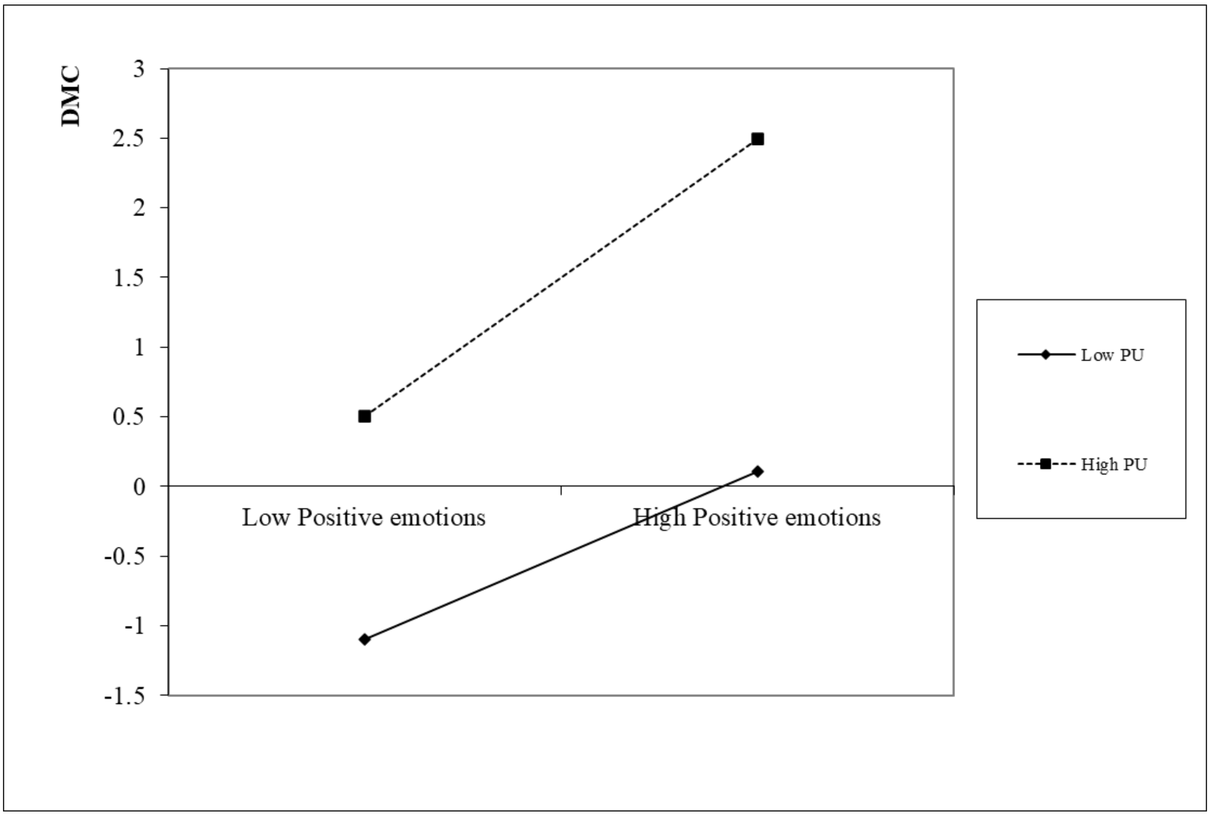

Figure 12. H4: PU×Positive → DMC

On the other hand, Figure 12 explains how PU moderates the relationship between Positive Emotions and Diverse Music Consumption. The plot shows a steeper and positive gradient for high PU as compared to low PU. Thus, this shows that the impact of positive emotions in increasing diverse music consumption is stronger when the recommender system is perceived as more useful. Users experiencing positive emotions may be more engaged with the platform and more receptive to its recommendations. When the recommender system is perceived as useful, this heightened engagement can translate into an increased likelihood of listeners of letting the recommender system of their preferred music streaming service help discover new and diverse music. These findings are in line with the discussion on how perceived usefulness is a critical contributor in users' acceptance of a recommender system (Armentano et al., 2015). Finally, as already found by previous studies, perceived ease of use does not have a great impact in the adoption of a new system (Armentano et al., 2015). Accordingly, H5 is not supported. As for H6, which is supported, Figure 13 shows a steeper and positive gradient for low PEOU as compared to high PEOU. This reveals that the impact of positive emotions in increasing diverse music consumption is stronger when the recommender system is perceived as more difficult to use. In this case, positive emotions can act as a buffer against the frustration experienced when dealing with a difficult-to-use system. Users experiencing positive emotions might be more patient and open to experimentation, leading to an increased consumption of new and diverse music to compensate for the system's shortcomings.

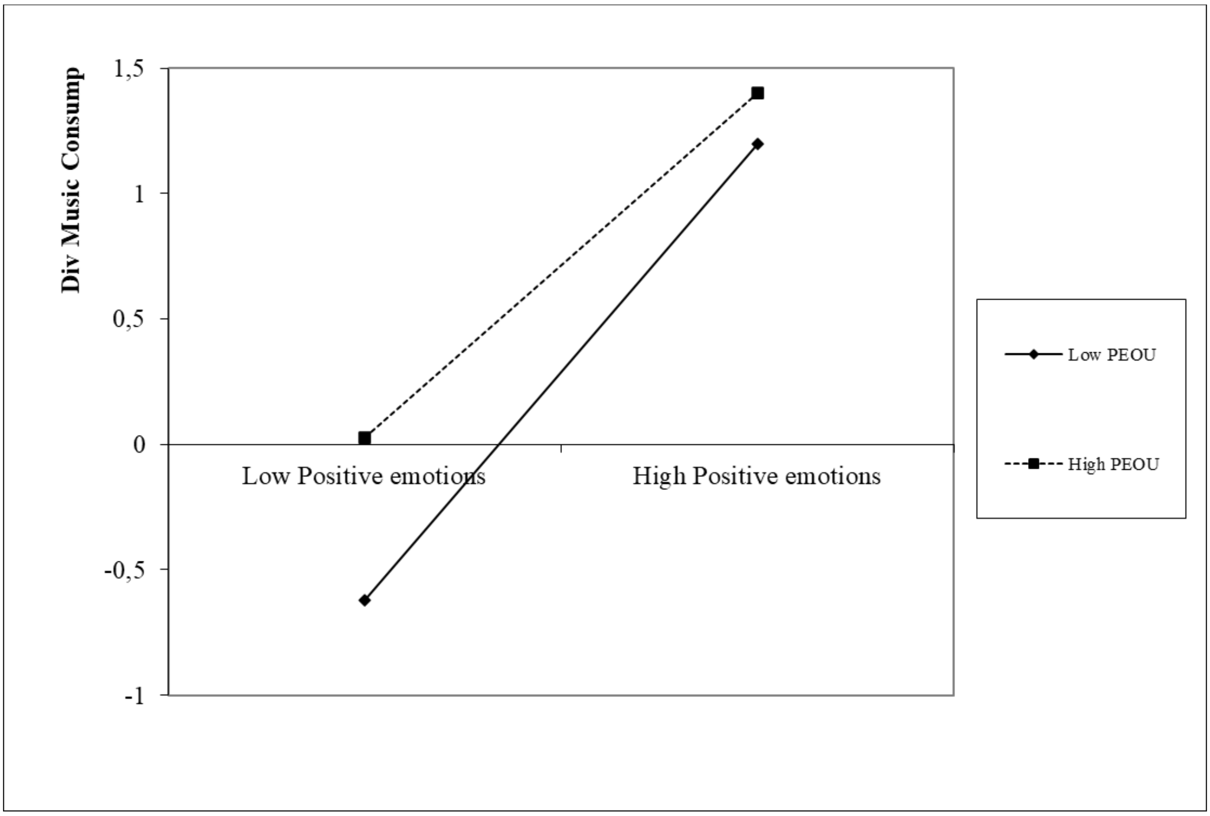

Figure 13. H6: PEOU×Positive → DMC

5.4.1 Theoretical implications

This study’s findings enhance the current understanding by providing empirical support for the importance of emotions on listeners’ diverse music consumption. Although extensive research has been done on the emotional motivations of music listening, little research has been done on how positive and negative emotions influence the consumption of new and diverse music. Therefore, this study is amongst the first attempts to identify a relationship between positive and negative emotions and diverse music consumption. Researchers can build on our framework to further explore associations between emotions and diverse music consumption, for example by studying which music genres are explored and consumed by people experiencing positive emotions and which are explored by those experiencing negative emotions.

In addition, this study also examined how perceived usefulness and perceived ease of use of music streaming services’ recommender systems, the main factors of the Technology Acceptance Model, moderate the effects of positive and negative emotions on diverse music consumption. This is especially important as music streaming services are the main medium of music consumption today. Indeed, even though many studies have applied the Technology Acceptance Model to the evaluation of recommender systems of video streaming services, almost no recent research has been done on the evaluation of those of music streaming services. As our findings provide support for the moderating effect of the main factor of TAM on the relationship between positive and negative emotions and diverse music consumption, further research could explore how this moderating effect changes when comparing different music streaming services, such as Apple Music and Spotify.

5.4.2 Practical implications

Given that our results revealed a positive correlation between positive and negative emotions and diverse music consumption, streaming services could implement a feature where consumers can express their current feelings, so that the recommender system can suggest them music accordingly. Moreover, since we found out that when people are experiencing negative emotions tend to seek music on their own, implementing this feature could help suggest more relevant music and led to consumers perceiving it as more useful.

In addition, as our findings show that the impact of positive emotions in increasing diverse music consumption is stronger when the recommender system is perceived as more difficult to use, music streaming services should work toward making the recommender system more accessible and fixing its shortcomings.

All these adjustments and improvements will help further increase consumers’ music consumption on music streaming services and make users more dependent on them as their main medium for listening to music.

6 Conclusion

Apart from the theoretical and practical implications, study limitations must be acknowledged. First, most of our respondents were from Europe and between the ages of 18 and 24, so further research could explore if age and nationality have a moderation effect on the relationship studied. The scope of this study was also somewhat limited by the sampling methodology and sample size. We used convenience sampling, collected from social media, and the size of the sample was 242 respondents, which is quite a small sample. Hence, findings must cautiously be generalized to the general population. Future research might benefit from considering a more substantial sample size.

Moreover, this is a preliminary study seeking to understand the relationship between emotions and diverse music consumption and the moderating effect that perceived ease of use and perceived usefulness of recommender systems of music streaming services have on the relationship. Accordingly, we did not take into consideration which music streaming service was used the most by respondents: it would be interesting to explore this route as different results could arise from different music services as each has its own algorithm for the recommender system.

Concluding, the aim of this study was to understand the relationship between positive and negative emotions and diverse music consumption. We have started from an overview of the history of the music industry to showcase the significant impact that music streaming services had and have on the business. Indeed, these platforms, equipped with complex recommendation systems, have completely transform the way we discover and consume music, leading us towards an era of personalized music experiences. Then, we presented the Technology Acceptance Model to introduce readers to the variables moderating the relationship between emotions and diverse music consumption. And finally, our theoretical investigation was closed by explaining the important role that both positive and negative emotions have in how we engage with music.

Results from our empirical research not only validated all of our hypotheses except one, but also offered fresh perspectives, enhancing our understanding of this multifaceted interaction. We can, then, imply that both positive and negative emotions increase listeners' diverse music consumption. This may be derived by a need to regulate or maintain certain moods or emotions, but also as a need to use music as a form of distraction or escapism in the case of negative emotions. Further research on the topic could also explore whether positive and negative emotions increase the overall time spent listening to music in general.

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Summary

This dissertation acknowledges the dramatic shift in the music industry due to the rise of streaming services like Spotify, Apple Music, Amazon Music, Tidal, YouTube, etc. Indeed, these platforms have become the primary income source for recorded music, with 74% of people consuming music through licensed audio streaming services. The industry's transformation is not just about consumption methods but also the emotional impact music has on listeners. Thus, this dissertation aims to understand the complex relationship between positive and negative emotions and diverse music consumption in the context of this rapidly evolving industry. It will also investigate the moderating effect of perceived ease of use and perceived usefulness (TAM factors) in the context of the music streaming services' recommender systems on the relationships between emotions and diverse music consumption. In order to do that, there will be three introductory chapters. Chapter 2 provides an overview of the music industry's history, focusing on the rise of music streaming services and their recommendation systems. It also examines the changing trends in music consumption in the digital age. Chapter 3 explores models of technology diffusion and acceptance, which can help us understand why and how new technologies, such as music streaming platforms, become popular and accepted by users. Finally, Chapter 4 explores how emotions affect the music-listening experience. It provides a background on emotional theory, explores the relationship between music and its listeners, and highlights the emotional motivations behind music consumption. Then, the last chapter presents the findings of the dissertation's research, discussing the research methodology, results, and their theoretical and practical implications. While the conclusion just presents the limitations of this study and gives suggestions for possible future research on the topic.

The history of the music industry is deeply intertwined with technological innovations, starting with the invention of the phonograph by Thomas Edison in 1877. This groundbreaking device marked the advent of sound recording and playback, leading to the birth of record labels and the commercialization of music. Then, in the early 20th century, the music industry underwent another significant transformation with the introduction of radio broadcasting. This technology made music accessible to millions of households simultaneously.

The digital revolution of the 1980s brought about another transformative phase. Digital recording technology gave artists new ways to create and manipulate music. Meanwhile, the rise of compact discs (CDs) led to lower production costs and hence, cheaper music prices for consumers. The 1980s also saw the launch of the Music Television Network (MTV), which popularized music videos and expanded the music industry's reach.

The 1990s brought the prominence of CDs as the main music format, causing a decline in cassette sales and the near extinction of vinyl. But then, the launch of Napster in 1999, a peer-to-peer file-sharing application, marked a significant shift as music had officially moved to the internet. This change initially led to a fall in recorded music revenues as record labels struggled to adapt. As the 21st century began, digital marketplaces like Apple's iTunes emerged to give a solution to illegal music downloads, which became popular after the launch of Napster. However, despite these efforts, US recorded music revenues fell nearly in half between 2000 to 2010, due to the sharp decline in physical sales and slower than expected adoption of digital sales.

The turning point came with the introduction of Spotify. The service, founded on the idea that convenient access to music was more important than personal ownership, proved successful. Indeed, following the advent of music streaming services, global recorded music revenues began to grow again in 2015 after over a decade of decline. By 2022, global recorded music revenues reached $26.2 billion, with streaming services accounting for approximately 67% of the total market.

Music streaming services operate on a relatively recent business strategy that essentially offers two forms of service: registration of a free account, where users are subject to advertisements and various limitations (freemium model), or, in contrast, users pay a monthly fee, granting them unrestricted access to the service (premium model).

Major players in the music streaming market include Spotify, Apple Music, Amazon Music, and YouTube Music. Each of these services provides a similar experience, allowing users to browse a large music library, create playlists, and discover new artists. However, because of competition, many services started to offer exclusive content, such as live recordings, concerts, interviews, to attract more users.

Recommendation systems are one key factor contributing to the success and popularity of music streaming services as they help users navigate the vast music catalog that the platforms offer. These systems gather users' preferences, which are either clearly expressed or deduced by interpreting users' actions, and then provide suggestions for items to be of use to a user such as products, music, news articles, among others. Hence, recommendations are personalized, so that different users receive diverse suggestions. There are two main approaches for building recommender systems, which rely on two different kinds of data: collaborative filtering methods use user-item interactions, like ratings, while content-based recommender methods use utilize the attribute information about the users and items, such as relevant keywords or textual profiles. Some recommender systems develop hybrid systems by fusing these two different methods. Hybrid systems can combine the benefits of multiple recommender system types to provide techniques that work more effectively in a wide variety of settings.

Music recommender systems (MRS) in the music industry are distinctive due to several factors, including the duration of consumption, the size of the catalog, varying levels of abstraction, repeated and sequential consumption, passive consumption, and the emphasis on content descriptions. These systems provide personalized recommendations based on past user interactions and aim to balance factors such as similarity versus diversity, novelty versus familiarity, popularity, trendiness, and the unexpectedness of music choices. For enhanced user satisfaction, MRS must evolve, integrating new technologies.

Finally, by enabling users to more easily access and explore a wide catalog of music, the rise of streaming platforms has significantly impacted music consumption patterns. Prior to the digital revolution, discovering new music required a considerable expense of time and money. Indeed, listeners had to travel to record stores and invest significant sums to buy albums in search of new and unknown artists. Other ways of discovering new music included going to shows of local bands, high-priced magazines, or friends living in other cities and countries.

Today, when discovering new music, users of music streaming services usually have two options: they can either discover music with user-guided search and exploration or through algorithmic recommendations – both of these alternatives require way less resources in terms of time and money. However, even if algorithmic suggestions and streaming platforms have revolutionized the accessibility of varied music, social media and human interaction continue to play a critical role in guaranteeing a truly diverse and rewarding musical experience. In order to build a more diverse and integrated global music landscape going ahead, it is crucial for the music business, artists, and consumers to find a balance between technology-driven and human-guided discovery.

Technology diffusion and acceptance are necessary steps of innovation and technological development, as they explain how new technologies are embraced and used by individuals, organizations, and communities. As technology continues to reshape our reality at an outstanding rate, consistently revolutionizing how we live, work, and interact, it is increasingly important to have a thoroughly understanding of the processes and elements affecting technology adoption and acceptance.

Technology diffusion refers to how new technology affects market dynamics over time. The Diffusion of Innovation Theory, popularized by Rogers, describes this as a process where an innovation is communicated through a social system over time. Key elements include the innovation itself, communication channels, time, and the social system. The theory outlines a typical 's-curve' of adoption where the innovation is slowly adopted, accelerates, and then gradually slows. Users adopt the innovation through a five-stage process: knowledge, persuasion, decision, implementation, and confirmation. Moreover, five categories of adopters were identified: innovators, early adopters, early majority, late majority, and laggards. Rogers further classified five attributes of innovation that can predict the rate of adoption: relative advantage, compatibility, complexity, trialability, and observability.

The Theory of Reasoned Action (TRA) describes how beliefs influence attitudes, intentions, and behavior. Two types of beliefs influence an individual's intention: those that influence perception of a particular behavior, and normative beliefs about what significant others think one should do. TRA was later extended into the Theory of Planned Behavior (TPB) by introducing perceived behavioral control (PBC) - an individual's perception of ease or difficulty of performing a behavior. This accounts for situations where individuals have no volitional control over their behavior. Finally, the Technology Acceptance Model (TAM) was introduced by Fred Davis. The TAM came into being due to the rapid growth of end-user computing in the early 1980s and had two main objectives: “to improve the understanding of user acceptance processes”, and “to provide the theoretical basis for a practical ‘user acceptance testing’ methodology that would enable system designers and implementors to evaluate proposed new systems prior to their implementation”. Davis suggests that the attitude toward using a given system is a function of perceived usefulness (PU) and perceived ease of use (PEOU), with PEOU having a direct effect on PU. Davis, then, goes on by defining perceived usefulness as “the degree to which an individual believes that using a particular system would enhance his or her job performance”. On the other hand, perceived ease of use is “the degree to which an individual believes that using a particular system would be free of physical and mental effort”. Despite being widely accepted, Davis’ model has been subject to criticisms over the years. For instance, Bagozzi argues that researchers have ignored crucial determinants of decision and action, favoring a more straightforward model. He noted large gaps between intents and behavior, as well as between PU and PEOU on the one hand, and intention on the other. Moreover, discuss how further research has only broaden the model, failing to deepen it in the sense of explaining PU and PEOU, or of introducing new variables to describe how the existing ones produce the effects they do.

The Diffusion of Innovations (DOI) and the Technology Acceptance Model (TAM) are key theoretical approaches to understanding technological innovation adoption. Both models operate on the assumption that adopters evaluate innovations on the basis of their perceived traits, suggesting that innovations boasting appealing characteristics are more likely to gain acceptance. Indeed, scholars usually associate the relative advantage feature of DOI to the perceived usefulness of TAM, and, at the same time, consider the complexity feature of DOI to be extremely similar to the perceived ease of use concept of TAM. This suggests that these models confirm each other’s findings as well as complementing each other. So, researchers believe that combining TAM and DOI could lead to the creation of a stronger model with satisfactory results. Consequently, some researchers have integrated TAM with DOI's compatibility feature, which affects perceived usefulness and intent to use technology.

Defining "emotion" remains contentious within the scientific community, with a wide range of definitions existing. However, common consensus holds that emotions are generally short-lived, context-specific, and occupy our consciousness forefront. Theorists, such as Russell, propose that emotions exist within a two-dimensional space defined by valence (pleasure-displeasure) and arousal. Another major perspective claims that the basic elements of emotions are discrete entities. Starting from this research, Plutchik expanded it using the psychoevolutionary theory, which assumes there are eight basic emotion dimensions arranged in four pairs: joy vs. sorrow, anger vs. fear, acceptance vs. disgust, and surprise vs. expectancy. This model, called “Wheel of Emotions”, was proposed in 1958 and further expanded over the years to describe more complex emotions: those resulting from the combination of two or more basic emotions.

Listening to music is a universally pleasurable activity for human beings, and one of its main purposes is the emotional experience it provides. While some researchers question whether music can induce emotions, others state that it can elicit a broad spectrum of emotions, ranging from basic to complex. This could be through brain stem reflexes, evaluative conditioning, emotional contagion, visual imagery, episodic memory, or musical expectancy. Other factors influencing emotional response include the listener's mood, cultural background, preferences, musical style, and composer's arrangement. For instance, Schubert argues musical structure, or more specifically, combinations of musical features may account for a significant portion of emotions in music.

The Uses and Gratification Theory (U&G) is a media research approach that explores how individuals consume media, like music, to fulfill their needs. Early work in the U&G domain grouped audience reactions and then studied social and psychological factors influencing media use. Katz, Blumer, and Gurevitch's framework, developed in the 1970s, suggested that audiences were proactive and strategic in their media choices to satisfy their needs. Moreover, the motivations for media use were grouped in terms of: diversion (e.g., as an escape from routine or for emotional release); social utility (e.g., to gather information for conversations); personal identity (e.g., to reaffirm attitudes, beliefs, and values); and surveillance (e.g., learning about one’s community, events, etc.).

The research conducted by Katz and his colleagues supplied the theoretical groundwork for the building of the Uses and Gratifications approach. The study of this topic has since been deepened and expanded to investigate the different types of media. Indeed, the U&G approach has been applied to music consumption research, providing valuable insights into the motives that bring individuals to listening to music. These are grouped into six main motivations: positive and negative mood management, diversion, interpersonal relationships, personal identity, and surveillance. Researchers have gone further to explore these motivations, finding that music acts as a versatile tool for mood regulation, especially in teenagers. Saarikallio and Erkkilä identified seven distinct regulatory strategies: entertainment, revival, strong sensation, diversion, discharge, mental work, and solace. Another perspective from Chamorro-Premuzic and Furnham links personality traits with musical preferences and the ways people use music, identifying three main categories: rational/cognitive appreciation, emotional regulation, and background to other activities.

Research has shown that people's motivations for listening to music can be influenced by both positive and negative emotions. Positive emotions, associated with wellbeing or happiness, typically occur in safe situations, whereas negative emotions serve as protective responses to threats. A study in 2019 found that upbeat and rhythmic music is used boost positive emotions, suppress negative emotions, and increase arousal. Results from the same study also tend to suggest that people may consume diverse music for different emotion regulation strategies.

Randall and Rickard in 2017 discovered that emotional reasons for listening to music were more common when the individual was in a negative mood. They also found that background music was the most popular reason for listening to music, and passive listening was more frequent than active listening, except when listeners were in a negative mood. They explained that this aligns with the view that listening to music is mainly a solitary, self-regulatory activity that helps people select music suitable for their mood and situation.

Regarding the use of music as an emotional self-regulating tool, Chin and Rickard found that consuming music to regulate emotions seems to be consistently more effective for one’s well-being than listening to music to repress emotions. Their results also show that increasing the amount of music consumption, if done with the purpose of suppressing emotions and thoughts, may lead to undesirable outcomes for one's well-being.

In this last chapter, the scientific paper is presented. It starts off with the development of the hypotheses based on the literature review done previously. It explores the connection between music and emotions, using the Uses and Gratification (U&G) theory. Also, theories such as the Theory of Planned Behavior and U&G have been used to understand music streaming behaviors. Entertainment/mood management and social interaction motives significantly predicted music streaming intentions. Moreover, in predicting the duration of time devoted to music streaming services, the TPB attitudes and social interaction motivation were significant predictors, and the addition of motive components substantially improved the predictive power. Based on the literature, the study proposes the following hypotheses:

H_1: Negative Emotions have a positive and significant impact on users' Diverse Music Consumption.

H_2: Positive Emotions have a positive and significant impact on users' Diverse Music Consumption.

Using the TRA as its foundation, the TAM focuses on understanding users' acceptance of technology. It argues that a person's intention to use a technology, which ultimately predicts their actual use of it, is determined by two main factors: perceived usefulness (PU) and perceived ease of use (PEOU). Various studies have used the TAM to assess user acceptability in recommender systems for a variety of goals. For example, Hu and Pu evaluated a personality-based recommender system for movies using the Technology Acceptance Model. Their results confirm that perceived accuracy plays a dominant role in determining user acceptance of a recommender system, while perceived ease of use shows a substantial correlation with users' acceptance intents and perceived accuracy. Thus, considering the results of previous studies, we formulate the following hypotheses:

H_3: Perceived Usefulness of recommender systems in music streaming services moderates the relationship between Negative Emotions and Diverse Music Consumption.

H_4: Perceived Usefulness of recommender systems in music streaming services moderates the relationship between Positive Emotions and Diverse Music Consumption.

H_5: Perceived Ease of Use of recommender systems in music streaming services moderates the relationship between Negative Emotions and Diverse Music Consumption.

H_6: Perceived Ease of Use of recommender systems in music streaming services moderates the relationship between Positive Emotions and Diverse Music Consumption.

Then, a comprehensive conceptual framework is presented based on the study's literature review, encapsulating the theoretical perspectives, hypotheses, and relationships involved in their research.

Following this, the study continues by presenting the research methodology. This study used a questionnaire developed on Qualtrics XM, divided into four sections: demographics, music medium preferences, usage of music recommender systems, and emotional responses to music. Responses were rated on a 5-point Likert scale. The appropriateness of the factor analysis for these items was assessed using the Kaiser/Meyer/Olkin (KMO) test and Bartlett's test of sphericity. Both confirmed the validity of the questionnaire items. Moreover, in the course of the exploratory factor analysis, items that did not sufficiently load on a specific factor (<0.40) or had cross loadings were expected to be removed. However, as all items had loadings exceeding 0.40, no deletions were necessary.

The questionnaire was distributed on social media, focusing on age groups with the highest music streaming service usage according to a 2022 report by IFPI and social media usage data from 'We Are Social'. A total of 242 responses were collected and included at the final data set, exceeding the required sample size of 204 for 95% confidence level and ±7% precision level. Although self-administered surveys are one of the most frequently utilized techniques in the social sciences, they also introduce the risk of common method variance and bias. Consequently, we used different methods to verify that our study is free from method bias, and it was found not to be an issue.

Data was analyzed by using SPSS version 26.0 for carrying out the descriptive statistics and reliability analysis on the gathered data, as well as for evaluating the demographic characteristics of the sample and the internal consistency of the constructs. Following this, the research model was analyzed using Partial Least Squares (PLS) analysis with the assistance of SmartPLS 3.0 software. For this study, a Partial Least Squares-based structural equation modeling (SEM) was employed to model and estimate intricate relationships among several dependent and independent variables, also referred to as PLS path modeling. Finally, to validate the significance of the path coefficients and the loadings, we employed a bootstrapping method (5000 resamples).

Then, results were presented and discussed in the next section. In terms of model validation, all item loadings, Composite Reliability (CR), and Average Variance Extracted (AVE) values surpassed their respective thresholds, suggesting strong convergent validity. Cronbach's alpha values, indicative of construct reliability, were also satisfactory. The study further confirmed discriminant validity using both Fornell and Lacker's method and the heterotrait-monotrait ratio (HTMT) of correlations.

The study revealed that both negative and positive emotions significantly affect diverse music consumption, supporting Hypotheses H1 and H2. The PU of music streaming recommender systems was found to moderate both these relationships. Conversely, PEOU had a significant moderating effect only on the relationship between positive emotions and diverse music consumption. Therefore, Hypotheses H3, H4, and H6 were confirmed, but H5 was not.

Having summarized the key findings of this study, it is now crucial to delve deeper into their meaning and implications. Support for our first hypothesis comes from studies indicating that individuals experiencing negative emotional states tend to engage in more active and emotionally charged listening experiences. In these situations, music consumption may serve several purposes, such as mood regulation, emotional discharge, and solace. People who are experiencing negative emotions may seek out diverse music to find what resonates with their feelings or gives them the desired emotional relief. Moreover, negative emotions, such as boredom and frustration, can drive listeners to seek novelty as a form of distraction or escapism.

Our second hypothesis is supported by the discussion on how music consumption contributes to emotional regulation and provides a background for various activities. People in positive or neutral emotional states may engage in more passive listening experiences, using music to maintain or boost their positive feelings. Diverse music consumption can provide different types of positive experiences, such as relaxation, excitement, or pleasure, depending on the listener's context or preferences. Moreover, positive emotions can foster curiosity and openness to new experiences. Thus, in both cases, emotions can lead to increased consumption of new and diverse music.

Regarding the moderating effects of the factor of the TAM on the relationship between emotions and diverse music consumption, we have obtained the following results. The impact of negative emotions in increasing diverse music consumption is stronger when a recommender system is perceived as less useful. Indeed, as previously discussed, users experiencing negative emotions might be more inclined to seek new and diverse music as a means of mood regulation, hoping to find songs that can help them alleviate or express their emotional state. Thus, when users perceive the recommender system as less useful, they may have lower expectations for the music suggestions provided by the platform. Then, it was found that the impact of positive emotions in increasing diverse music consumption is stronger when the recommender system is perceived as more useful. Users experiencing positive emotions may be more engaged with the platform and more receptive to its recommendations. When the recommender system is perceived as useful, this heightened engagement can translate into an increased likelihood of listeners of letting the recommender system of their preferred music streaming service help discover new and diverse music. These findings are in line with the discussion on how perceived usefulness is a critical contributor in users' acceptance of a recommender system. And finally, the impact of positive emotions in increasing diverse music consumption is stronger when the recommender system is perceived as more difficult to use. In this case, positive emotions can act as a buffer against the frustration experienced when dealing with a difficult-to-use system. Users experiencing positive emotions might be more patient and open to experimentation, leading to an increased consumption of new and diverse music to compensate for the system's shortcomings.

Finally, this section presents the theoretical and practical implication of the study, which is amongst the first attempts to identify a relationship between positive and negative emotions and diverse music consumption. Researchers can build on our framework to further explore associations between emotions and diverse music consumption, for example by studying which music genres are explored and consumed by people experiencing positive emotions and which are explored by those experiencing negative emotions.

In addition, this study also examined how perceived usefulness and perceived ease of use of music streaming services' recommender systems, the main factors of the Technology Acceptance Model, moderate the effects of positive and negative emotions on diverse music consumption. This is especially important as music streaming services are the main medium of music consumption today. Indeed, even though many studies have applied the Technology Acceptance Model to the evaluation of recommender systems of video streaming services, almost no recent research has been done on the evaluation of those of music streaming services.

As our findings provide support for the moderating effect of the main factor of TAM on the relationship between positive and negative emotions and diverse music consumption, further research could explore how this moderating effect changes when comparing different music streaming services, such as Apple Music and Spotify.
Given that our results revealed a positive correlation between positive and negative emotions and diverse music consumption, streaming services could implement a feature where consumers can express their current feelings, so that the recommender system can suggest them music accordingly. Moreover, since we found out that when people are experiencing negative emotions tend to seek music on their own, implementing this feature could help suggest more relevant music and led to consumers perceiving it as more useful.
In addition, as our findings show that the impact of positive emotions in increasing diverse music consumption is stronger when the recommender system is perceived as more difficult to use, music streaming services should work toward making the recommender system more accessible and fixing its shortcomings.
All these adjustments and improvements will help further increase consumers' music consumption on music streaming services and make users more dependent on them as their main medium for listening to music.

In the conclusion, limitations and suggestions for future research are stated. Indeed, most of the respondents were young adults from Europe, thus warranting further research to investigate potential moderating effects of age and nationality. The use of convenience sampling and a small sample size (242 respondents) further limits the generalizability of the findings.
Moreover, the study didn't account for which music streaming service respondents used the most, suggesting another area for future research, given the unique algorithms of different services.