LUISS

Degree Program in Marketing: Market Relationship & Customer Engagement

Course of **Product & Brand Management**

The influence of musical tempo variation on consumers' attitudes: the moderating role of the type of brand

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Abstract

This experimental study aims to investigate the relationship between musical tempo variations (slow tempo versus fast tempo) and consumer attitudes towards fashion brands. This study further examines whether the type of brand (luxury versus fast fashion) moderates this relationship and whether the fit between the background music and the type of brand acts as a mediator. The study presented a 2x2 between-subjects causal conclusive research design tested on a sample of 197 active respondents who took part in an online survey. Results indicated that luxury brands had a better effect on consumers when associated with slower tempo music compared to faster tempo music and a greater fit between the background music and the type of brand resulted in a stronger positive effect on consumer attitudes. Existing research regarding the effect on consumers of musical tempo variations in the fashion industry is limited, for this reason, this study contributes to the understanding of music stimuli implementation in the field of marketing and brand management.

Keywords: brand management, sensory marketing, musical tempo manipulation, fashion industry, background music

Introduction

More and more studies are proving the interconnection between the fields of marketing and music showing that these two areas of study can effectively be used together to achieve common objectives. In fact, research shows that music does indeed impact consumers and their emotions and, for this reason, marketers are implementing this research conducted on music and consumer behaviour as a means to develop effective marketing strategies that will aid sales and profitability. Musical stimuli are made up of various components that if altered individually, can evoke different emotional responses. Music is a form of communication, thus meaning that brands can use it to further communicate messages and their identity.

The aim of this research is to analyse the effects of musical stimuli through manipulation of musical characteristics (specifically musical tempo), on consumers' attitudes towards brands, specifically, fast fashion and luxury brands. The objective is to understand which combination of speed of music (fast versus slow) and type of fashion brand (luxury versus fast fashion) solicits consumers' attitudes in the most effective way.

Nowadays, the internet and globalisation have led to industries becoming fully saturated with brands, it therefore becomes crucial for brands to stand out from competitors. Brands need to communicate their uniqueness and it is in fact the case that the most recognisable brands, those with the strongest identities, are the brands that become icons. For this reason, the inclusion of sensorial stimuli is nowadays becoming more and more common, in fact, examples of auditory stimuli include Netflix and McDonald's jingles. Consumers can instantly recognise these brands without the need to look at the logos. Therefore, this research further aims to create greater understanding of how music can be used to a brand's advantage.
For the above reasons, this research will be divided into the following four chapters.

Chapter I will be looking at the use of marketing in the Arts and more specifically in the music industry. Defining key figures and providing a general overview of the industry. Subsequently, Chapter II will be reviewing previous research and available insights on the effects of musical characteristics manipulation and how these are being used to the present day. Chapter III will instead be reviewing Spotify's game-changing music recommendation system delving into the algorithm's ability to personalise recommendations for its users and how this changed today's music industry. Finally, Chapter IV will define the experimental study looking at the relationship of musical tempo variations and its effects on consumer attitudes towards fashion brands and whether the type of brand will act as a moderator. Additionally, the study will look at whether the fit between the background music and the type of brand will act as a mediator. This chapter will also summarise the results and its main findings.

Chapter 1: Marketing in the Arts, a focus on the music industry

1.1 Marketing in the Arts

1.1.1 Definition of marketing in the Arts

It is often believed that marketing can be applied to various fields, however, it is important to take into consideration the extent to which traditional marketing techniques apply and are adequate to all industries. In fact, when looking at the Arts industry, conventional terminologies used for products and services do not fully fit the description of the offerings. When referring, for example, to the music industry and more specifically to the promotion of a song, it is often the case that one may refer to this as the promotion of a product. However, a song, which is intangible, cannot receive the same type of treatment a physical product receives. For this reason, marketing for this type of intangible product necessitates a different consideration by marketers fundamentally involving a more inclusive multi-directional approach (Mičák, 2020).

Art can be defined as *"a documented expression of a sentient being, through or on an accessible medium, so that anyone can view, hear or experience it. If this solidified expression, or the act of producing it, is 'good' or has value depends on those who access and subjectively rate it."* (Hill et al., 2017). Marketing in the Arts must take into consideration the idea that the products being offered deliver an experience often guided by factors such as emotions. Therefore, in this case the perception of value is determined by the emotional involvement of the receiver, and for this reason, an indication of quality depends on the receiver's subjective experience when in contact with the piece of art.

For this reason, Arts marketing can be defined as *"an integrated management process which sees mutually satisfying exchange relationships with customers as the route to achieving organisational and artistic objectives."* (Hill et al., 2017). According to this definition, the achievement of the artist's objectives and the artist's delivered artistic performance are strictly related to the receiver's personal experience with the artistic performance. Thus, for this relationship to succeed in the realisation of the artist's intentions, marketers in the Arts industry must assure that both organisational and artistic objectives are aligned.

1.1.2 Scope of marketing in the Arts

Artistic performances are the product of an individual's creative process, it can therefore be inferred that anyone could develop their personal artistic performance and deliver it to the market. This means that, although all artistic performances differ from each other, the market is saturated with the same type of product. Especially nowadays, due to the exponential growth of technology and increased digitalisation, more and more artists have the possibility to develop their artistic performances. For a sector where supply far exceeds demand, marketers in the Arts industry have the fundamental role of communicating the artist's message and uniqueness while differentiating strategies from other artists in order to make their artist stand out among the competition (Colbert, 2009). Marketers also need to consider the different customer groups and the factors affecting their willingness to purchase and/or attend arts performances and, consequently, segment current and potential consumers and develop specific communication strategies to effectively target the different customer groups (Bernstein, 2006).

Furthermore, due to the emotional involvement of the audience when exposed to the artistic performance, marketing in the Arts needs to focus on establishing an emotional connection between the artistic performance and the audience in order to keep the audience hooked to the performance and engaged with the experience. For this to be achieved, a strong communication of the artist's message and targeting the correct audience represent fundamental elements for the achievement of the artistic objectives.

1.1.3 The importance of promotion in creative industries

As in most industries, a perfect product is of no use if customers are not aware of its existence. Consequently, promotion is the vehicle with which brands communicate their products to customers. Just like industries involving the promotion of tangible goods and/or intangible goods, creative industries, such as the Arts industry, require customers to be aware of the existence of an artist and all his creations.

An artist's customer/follower may be referred to as a fan; fans and, more specifically, the artist's fanbase are what determines the level of success of the artist. For this fanbase to grow it is important that the artist's marketing team effectively target the desired audience. For this reason, promotion should not solely focus on selling the artist but on communicating the artist's value. Promotion strategies should be thought of as part of the artist's narration, these aid the acquisition of new fans who resemble themselves in the message communicated by the artist.

1.2 An overview of the music industry

1.2.1 Definition and segmentation of the music industry

The music industry features individuals and organisations involved in the creation, distribution and sale of music (Shrm-Cp, 2023). The music industry can be segmented in various key roles, these being:

- **Artists/songwriters** – these being at core of the industry, artists/songwriters represent the creative element fuelling the music market. The results of their creations have a direct impact on the direction the music industry takes.
- **Music producers/Engineers** – these individuals help shape the sound and structure of a musical creation.
- **Record labels** – these support and fund artists by recording, managing and promoting artists' work. Record labels are also responsible for the discovery and signing of new artists, this is done by their A&R (Artist and Repertoire) team.
- **Music publishers and Distributors** – where publishers focus on the collection of royalties destined to songwriters for written works and distributors focus on delivering music to digital platforms and collecting royalties from sales of streams of the song recording.
- **Managers** – these oversee an artist's career and act as intermediaries between artists and other professionals in the music industry. Managers focus on the business side of an artist's career and negotiate deals in the artist's best interest.
- **Music attorneys** – these professionals focus on legal issues such as copyright, contracts, licensing and other disciplines regarding the music industry.
- **Streaming platforms** – to the present day, streaming platforms such as Spotify, Apple Music, Amazon Music and others have become major players in terms of music distribution.
- **Music education** – Institutions responsible for the music education of future musicians.

- **Music technology** – involving the hardware and tools used by the industry and subject to constant technological evolution.

1.2.2 Major changes in the music industry over the years

The music industry has faced many changes over the past years, among the most drastic is the way in which consumers listen to music. This is mainly due to technological advancements and the increased use of the internet. The evolution of the digital world has allowed for greater accessibility to music and led to a variation in the style of music consumption. Consumers have access to a greater number of songs and to a greater number of different genres. Furthermore, consumers are now able to listen to music from anywhere thanks to streaming services and the ability to digitally store songs anywhere.

Decades ago, radio stations were a common means to discover new music. In terms of purchasing music, vinyl records were the most common format to access songs from home. Consumers would have record players at home and would purchase their favourite band's records to listen to in their own time. Vinyl records were very popular between the 1950s through to the 1980s/1990s. Cassette tapes also became a major player between the late 1970s and the early 1990s only to be surpassed by the introduction of CDs in the 1990s. Consumers would buy CDs and play them in their CD players. The transition to the digital world evolved through the possibility of downloading/buying songs from platforms such as the iTunes store and storing them in portable devices such as the iPod. However, this represented a major issue for the industry as downloading music allowed for illegal pirating activity of music downloads. This represented a significant change in how music was consumed and, for this reason, led the way for the introduction of streaming services which, to the present day, represent the biggest form of consumption.

Technological innovation also caused structural changes in organisations. These switched from more traditional vertically integrated structures to delayered organisations involving outsourcing. Globalisation and the consequent increase in competition (also stemming from lower entry barriers for independent labels/artists) meant that covering a greater area of the market by owning many smaller labels and building up a larger artist catalogue allowed for greater flexibility and represented the best form of power for major labels (Renard et al., 2012).

There has also been a shift in how artists once used live performances as methods to advertise their new records as greatest profits would arise from the selling of records whilst nowadays, mainly due to streaming services drastically reducing royalties for artists due to their low monthly subscription plans, artists have a greater interest in using albums/records as a way to advertise their upcoming tours as these generate the highest level of income.

Furthermore, the music industry has faced various changes in terms of genres. Whilst previously artists would focus on one major genre, nowadays, thanks to the increased use of the internet resulting in greater globalisation and contamination, new genres have emerged and artists are much more versatile and able to blend different genres together. An example being the increased pop productions blending elements of the 1980s Disco music dominated by the use of synths and elaborate drum rhythms to today's catchy and effective melodies. In fact, music tends to be cyclical and this is an example of how today's industry is contaminated by genres and sounds that already were able to dominate the market for a previous generation.

Additionally, technological evolution further contributed to the current industry being saturated with artists. To the present day, more and more people have access to certain technological facilities which only few used to have access to and had the competencies to use. In fact, more and more people are able to produce songs; record them at home in a DAW (Digital Audio Workstation); use a variety of instruments thanks to virtual instruments; distribute and release songs without the need for a record label and all of this can be done on today's computers which have evolved significantly compared to older machines used. Consequently, this generates a greater number of songs being released by artists due to the market's lower entry barriers. This generational change from recording studio logic to a more digitalised approach is the product of Hip-Hop and EDM (electronic dance music) where artists adopt a more hands-on approach using samples and loops as tools to create their music gaining immense popularity and therefore developing a new generation of "do-it-yourself" artists who produce, write and record their own songs, roles which before were undertaken by different people (Reuter, 2022).

Another significant change occurring in the music industry takes into consideration the method of discovery of new artists with social media becoming a key player for an artist's marketing campaign. Social media platforms such as TikTok and Instagram are becoming more and more relevant when considering the possibilities to reach greater audiences.

Another important change that took place in the music industry is what people refer to as the "Loudness War". The "Loudness War" refers to a concept where audio levels of a music recording are increased to as close as possible to maximum peak levels in order to obtain a competitive advantage over other artists' music recordings. The reason behind this is that humans tend to perceive louder as better, so record labels and other professionals in the music industry push their artists' music recordings to as loud as possible in order to induce listeners into thinking that those artists' songs are better than other artists'. However, this audio practice leads to a loss of audio fidelity and loss of dynamic range which to more experienced ears represent an inferior quality and worsening of the track (Devine, 2013). In fact, the practice of dynamics compression results in a deterioration of the quality of the audio file (Vickers, 2010) whilst the greater the increase in loudness of a track, the greater the level of distortion of the audio file. This over-compression of the audio file means that tracks have no dynamics (Von Ruschkowski, 2008). Additionally, according to certain studies, higher loudness levels of new albums could potentially lead to increased harm to listeners' hearing. This is because, although certain streaming platforms (such as Spotify) bring all songs to the same volume so that listeners don't have to change their headphone volume depending on what song they're listening to, loudness can be thought of as an intensity/sound pressure. Therefore, the loudness of a track is a perceived volume and the greater the pressure applied to listeners' ears for a sustained amount of time, the greater the potential harm. Figure 1 and figure 2 (*Dynamics: What's Changed*, 2023) below depict two waveforms of two tracks showing the difference between a dynamic, quiet track and a loud track.

Figure 1: Depiction of the waveform of a dynamic, quiet track, “Thinking of you” by Sister Sledge (*Dynamics: What’s Changed*, 2023)

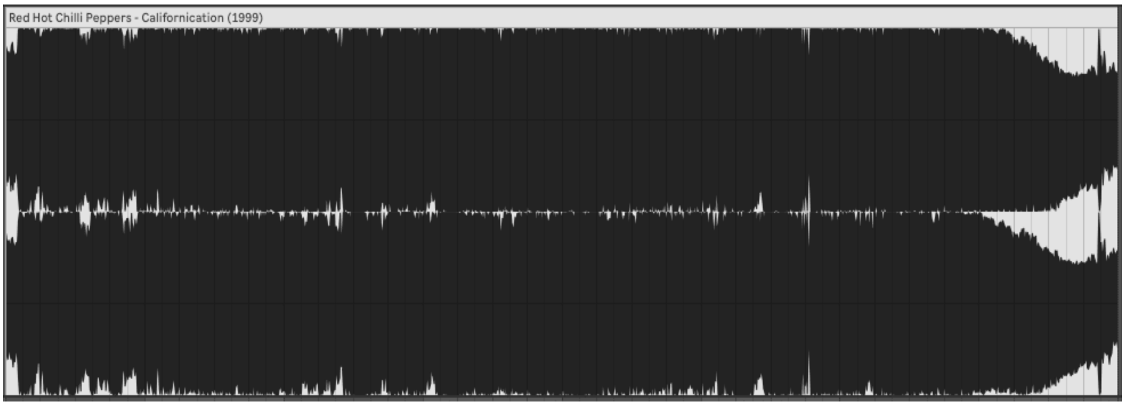


Figure 2: Depiction of the waveform of a loud track (also referred to as a brick-wall waveform due to its resemblance to an array of bricks), “Californication” by Red Hot Chili Peppers (*Dynamics: What’s Changed*, 2023)

Loud tracks started to gain popularity in the 1980s/1990s as a consequence of the proliferation of digital technology (Devine, 2013) and as a result of mastering engineers (where mastering refers to the final stage of audio production, it’s the process of balancing the sonic elements of a mixed track ready for distribution to the different platforms) learning how to optimise mastering for CDs. Nevertheless, this was nothing close to the number of loud tracks that can be found on the market today. The industry is split between audio engineers who adhere to what is the industry standard of loud tracks and engineers who are against it and fight for more dynamic tracks.

1.2.3 Trends in the music industry

There are various trends in today's music industry and all are highly influenced by constant technological advancements. In fact, the rise of social media and platforms such as TikTok have changed significantly the way the industry and artists engage with the audience leading to potential overnight viral hits which could generate short-term success. More and more artists are focusing on delivering quality content for these platforms. Furthermore, streaming platforms are the most common means of music discovery and consumption, artists can gain greater exposure if they manage to successfully engage with the platform's algorithm. It is also becoming quite usual to see different genre artists from different markets and countries collaborating on songs together. The objective of this is mainly to gain new listeners and followers from different markets and grow the artists' audiences. Additionally, with the increase in interest for the blockchain and NFTs, more and more artists are considering the possibility of raising funds through involvement with NFTs. For example, some artists such as "The Weeknd" have been releasing NFT projects featuring a full song of which the ownership of the recording will be transferred to the highest bidder and therefore winner of the auction alongside some The Weeknd-inspired artwork. Another similar involvement regards younger artists who sell portions of their royalty rights to investors in exchange for upfront liquidity that can be used to invest in the development of the artist's career. If the artist and his music were to succeed, the investors would gain from the royalty shares they own. Another more innovative emerging trend regards the integration of virtual reality. Nowadays, many famous artists have taken part in immersive music experiences managing to capture a greater amount of people due to the possibility of engagement with fans globally, no matter the number of people and the geographical location.

1.3 Marketing in the music industry

1.3.1 Definition of music marketing

Music marketing refers to marketing activity specifically applied to the field of music. In fact, it can be defined as, *"the act and process of creating, sharing, delivering, and exchanging music offerings that have value to customers, fans, or partners."* (McCulloch, 2022). This is an adaptation of the American Marketing Association's (AMA) approved definition for marketing. Analysing this definition, music marketing is about communicating to an audience an artist’s music and delivering value to fans in exchange of consumption of the artist’s music. The objective of music marketing is to establish a fan base and stimulate engagement with the aim to increase sales.

1.3.2 Marketing tools used in the music industry

There are various marketing tools that can be used in the music industry, nonetheless, these differ depending on the level of commitment and engagement of the customer. Figure 3 (Clifford, 2018) illustrates a fan funnel depicting the four stages of fan engagement. The first stage being the stage of “Discovery”, these are fans that don’t know much about the artist and happen to come across the artist’s music and, therefore, are attracted to the artist’s music. The next stage refers to “Casual fans”, these are fans that follow and actively listen to the artist’s music despite not necessarily purchasing any products therefore engaging with the artist. The following stage refers to “Buyers”, these are supporting fans that show their commitment towards the artist by purchasing the artist’s products such as merchandise and tickets for live events and therefore convert their interest into purchases. The final stage of the fan funnel refers to “Super fans”, these are fans that are regular supporters and act as the artist’s advocates and therefore retain their interest in the artist. It is important for artists to develop “Super fans” as these provide a constant source of steady income also in periods where ancillary sales could potentially fall due to unforeseen events such as COVID-19 forcing all artists to cancel their scheduled tours (Alam, 2021).

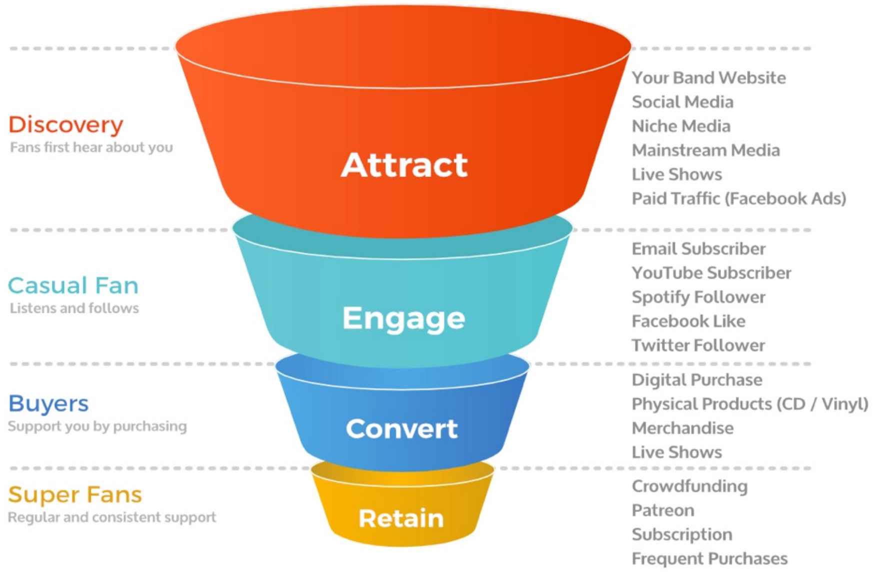


Figure 3: Depiction of the fan funnel, (Clifford, 2018)

Different tools can be used for the different stages of the fan funnel. For example, starting from the attraction phase, social media platforms such as Instagram, TikTok and Facebook can be used as an accessible method to reach a larger audience due to their extremely large user-base. These platforms also allow for promotion to take place, examples including Facebook and Instagram Ads which provide artists with the possibility of selecting and constructing their target audience to then target it. Live shows are another form of discovery as people who never came across artists could discover them at their local venues. Also, listening to live arrangements compared to recorded versions of songs can shed a new light on songs which listeners may not have necessarily liked prior to the live show. Additionally, due to the technological advancements in streaming platforms' algorithms which allow platforms such as Spotify and Apple Music to craft playlists and song suggestions for customers according to their musical taste, artists could be featured in these personalised playlists.

For what regards the engagement phase, once again, social media platforms act as the best form of engagement generation. Consistent posting and interactive content can act as stimulators for fans to engage with the artist. Additionally, social media platforms allow for user-generated content (UGC) which further emphasises engagement by other users who want to be part of a trend.

Regarding the conversion phase, merchandise is the most common form of fan conversion. Fans often purchase merchandise with the intention to have something

personal, something which brings them closer to the artist and that can support the artist. Limited edition products or vinyls/CDs act as something physical fans can own, therefore reducing the distance between the fan and the artist. Once again, live shows also represent a form of conversion as purchasing tickets to attend the live event can convert fans into actual followers.
Finally, regarding the retaining phase, subscriptions or crowdfund platforms (such as Patreon) allow fans to constantly support their favourite artists by contributing monthly fees and in return receive exclusive content. Other forms of retainment include the creation of private groups or fan clubs where fans can directly interact with the artist.

1.3.3 Impact of marketing in the music industry

Behind every hit single lies a great composition, nonetheless, if people don't have access or are not aware of the existence of the composition, then the song will never reach its true potential. For this reason, marketing plays a major role in the success of a song as it gives the artist and his music exposure. This is especially true nowadays due to the evolution of the digital world and the possibility for artists to reach a greater audience. The digital age has also contributed to increased levels of engagement through social media as these allow for greater user involvement, in fact, marketing teams develop artist strategies with the aim of building long-lasting relationships with the artist's fans. It is also easier to establish a point of contact with artists through features such as direct messages (DMs).

Nevertheless, for sure the evolution of the digital world has aided artists to reach greater audiences, however, this means there is also greater competition as so many artists enter the market every day. For this reason, the concept of branding for artists comes into play. Artists such as The Beatles, Michael Jackson and The Rolling Stones that manage to stay in time and become cultural icons are those that are instantly recognisable, these artists are a brand themselves. The reason why these artists have been so revolutionary and influential that people instantly recognise them and acknowledge them as if they were a brand is because of their strong brand identity. The marketing team behind each one of these artists was able to fully communicate the artist's message to the people and helped in the creation of cultural icons. The importance of promotion in today's highly connected and fast-moving world has in fact demonstrated that artists and their music are not single commodities but also instruments of promotion generating profitability from a variety of different sources of revenue (Meier, 2017). Proficient marketing efforts can turn a successful national artist into an acclaimed international artist. This can be the case of Scottish singer-songwriter Lewis Capaldi. At the start of his career, Lewis Capaldi and his team noticed that based on his genre and the already saturated UK market, it would have been hard for a new entrant to establish himself in the market. For this reason, Capaldi signed a record deal with the German division of Universal Music Group. Due to the lower barriers to entry, Capaldi got the help and attention he needed to develop his career and rapidly started climbing the charts. Capaldi went on to become an international sensation and, to the present day, is one of the most popular artists worldwide with multiple songs reaching over one billion streams on streaming platforms such as Spotify.

1.3.4 Marketing opportunities for upcoming artists

Upcoming musicians can exploit the potential of social media platforms' algorithms to develop their career. In fact, many artists have started their careers through social media. Among all, TikTok is the platform with the highest chances of generating overnight success due to viral content and this is mainly due to its algorithm which does not prevent users with a small number of followers from reaching large audiences. An artist who paved his way in the music industry through TikTok is Lil Nas X whose hit single "Old Town Road" became viral on TikTok and stimulated user-generated content leading to his debut single totalling over one billion streams.

Another platform which is starting to grow in terms of users is Twitch. Twitch is a video live-streaming platform which is not yet saturated with creators. Potential opportunities for upcoming artists could show up on this platform as not many artists are using it to reach new audiences. Examples already exist of content creators such as IShowSpeed who used Twitch as a platform to become a global entertainment phenomenon. Musical artists could replicate a similar business model to market their music and grow their audience through the likes of Twitch and other emerging platforms.

For sure, the advent of new technologies allows artists to adopt a more “Do-It-Yourself” approach making the role of an artist more and more similar to that of an entrepreneur. In fact, entrepreneurs tend to individually cover more roles in reward of greater control and freedom. This can be mirrored in music where artists are able to produce their music; distribute and promote it. Of course, this results in greater control of what the artist is communicating and delivering to the public, alongside greater freedom regarding when to deliver it. Nevertheless, this comes with a greater risk as artists do not have the market power and capital a major label has to effectively market their music. Therefore, the growth of the internet for sure provides opportunities for more artist-entrepreneurs to access the market with their music but this does not come without a greater risk of not managing to effectively reach the desired audience (Peltz, 2011).

1.4 Digital marketing in the music industry

1.4.1 Definition and scope of digital marketing in the music industry

Digital marketing refers to the implementation of different digital channels to market a product or brand to consumers. The purpose of digital marketing in the music industry is to market artists/music to the public through digital channels such as Search Engine Marketing (SEM) and Search Engine Optimisation (SEO); social media marketing; e-mail marketing and many more. Record labels can use digital marketing to diversify their means of targeting and maximise their audience reach due to the extremely large number of users who have an online presence. For this reason, considering the immense potential and possible reach of the internet, for an artist, developing an online presence is no longer considered a promotional instrument but a direct necessity to generate profit (Stafford, 2010). Furthermore, digital channels allow for greater and more accurate consumer targeting as, through the implementation of cookies and analytics, consumers can be segmented and targeted based on their musical tastes and other factors such as demographics.

1.4.2 Evolution of music marketing in response to technological advancements

Technological advancements shape how music is promoted and artists adapt according to the latest trends dominating the industry. Over the years, different technological waves forced drastic strategic changes in the way music is promoted. Starting from the 1920s, radio stations were dominating the market and represented the main form of entertainment. The public would be listening to radio stations for hours, consequently making radio broadcasting the best form of music discovery and greatest opportunity for an artist to reach a new audience. Later, from the 1950s through to the 1980s, the television replaced radio as the main broadcasting medium causing marketing efforts to focus on a more visual approach, thus leading to the increased presence and popularity of music videos in the 1980s on platforms such as MTV. Following the 1980s came a real shift from analog to digital leading to the introduction of the internet. Consequently, marketing strategies switched to digital promotion and growing an artist's digital presence with the aim to reach and connect with as many users as possible. Over the last twenty years, different forms of digitalisation took place causing smaller adaptations in marketing strategies, for example, looking at the transition to streaming platforms and marketing strategies focusing on driving song streams and soliciting the platforms' algorithms to generate even more streams; or the increased use of social media leading artists to focus on engaging as much as possible with users; or more recently, the introduction of the blockchain and NFTs giving birth to new forms of royalty payments and ownership.

Chapter 2: Characteristics and effects of musical stimuli on consumers

2.1 Music features definition

There are various features that compose a musical stimulus and that are used to describe it, the direct manipulation of these can generate different reactions in consumers.

Pitch

Pitch refers to the "*position of a single sound in the complete range of sound*" (Britannica, 2023). In music, a single sound is referred to as a note. A sequence of notes is defined as a melody (Oxenham, 2012). Young humans with healthy hearing are able to perceive frequencies (expressed in Hertz – Hz) approximately between 20 and 20,000 Hz. Terminology to express verticality is commonly used to describe pitch. "High pitch" refers to a sound closer to a higher frequency in the sound spectrum whilst "Low pitch" refers to a sound closer to the low-end of the frequency spectrum. Therefore, movements in pitch can either be ascending or descending.

Harmony

Harmony refers to combinations of notes played at the same time (Oxenham, 2012). This simultaneous combination of notes results in either consonance (when the two or more notes played together create a sound that is pleasant to the listener's ear evoking a sense of stability) or dissonance (when the two or more notes played together create a sound that is unpleasant to the listener's ear evoking a sense of tension). Relationships between the notes define the consonance or dissonance of the harmony of a musical piece (Bruner, 1990).

Mode

Mode refers to a progression of notes. The distance between each note in the progression is referred to as an interval. The specific succession of intervals starting from the tonic (the central note of the tonality) will generate a type of scale (a mode). The most utilised modes are referred to as the Major mode (also known as the Ionian mode) and the Minor mode (also referred to as the Aeolian mode). These modal scales provide for the tonality of a composition (Bruner, 1990). Tonality is the *"principle of organising musical compositions around a central note, the tonic"* (Britannica, 2023).

Tempo

Tempo refers to the speed of a musical piece and is expressed through numerical notation known as BPM (Beats Per Minute). The BPM provides musicians with an indication of the pace at which the musical composition needs to be performed. Subjective terms (such as *allegro, adagio* or *vivace)* are used to express BPM ranges (Quinn and Watt, 2006). For example, *allegro* represents a tempo approximately ranging between 120 and 156 BPM. Slower tempos are generally associated with sadness whilst faster tempos are associated with happiness (Levitin et al., 2018).

Rhythm

Rhythm looks at the organisation and distribution of accents in a musical piece, in fact, it can be defined as the pattern of accents in relation to the unaccented beats of a musical piece (Cooper et al., 1963). Rhythm has a strong cognitive function, it is responsible for the communication of the *"musical meaning"* of a composition as it guides the listener's attention through the different musical events that will take in the composition (Thaut, 2013).

Texture

Texture looks at the layering and richness of a musical piece (Bruner, 1990). It is the structural relationship among the different layers or parts (Covach, 2018) shaping the overall sound of a musical piece.

Timbre

Timbre is an element of texture and represents the perceived quality of a sound. It looks and describes the tonal differences with regards to how the same note or pattern of notes sound different according to the instrument playing them (Bruner, 1990).

Volume

Volume also is an element of texture and refers to the degree of intensity of a sound or how loud it is. Volume is musically interpreted through dynamics which guides instrumentalists into playing different notes at different intensities (and therefore at different volumes).

2.2 Music effects on mood

2.2.1 Effects of changes in tempo

Various studies have looked at the effects of tempo manipulation on consumer mood. A study conducted by Hevner (1937) looked at the effects of fast and slow tempo on subjects. Findings suggested that slow tempo evoked feelings of tranquillity, sentiment and solemness whilst fast tempo evoked feelings of joy and exhilaration. An initial study conducted by Rigg (1940a) looked at the influence of musical tempo on emotions and its ability to act as a determiner of musical mood. The experiment consisted in exposing participants to five musical phrases (of which three considered to be in a happy mood and the remaining two in a sad mood) and playing them at six different metronome speeds. Results confirmed that the faster tempo resulted in a happier perception of the music whereas the slower tempos were perceived as making the music sadder. A study conducted by Fernández-Sotos et al. (2016) looked at the influence of tempo and rhythm on emotions. The study focused on note value which specifically refers to rhythm through two experiments, experiment I looked at the influence of tempo whilst experiment II the influence of rhythmic unit. Participants were asked to label musical fragments by using words with opposite meanings belonging to four semantic scales, these were: *"Tension"* (words ranging from *Relaxing* to *Stressing*); *"Expressiveness"* (words from *Expressionless* to *Expressive*); *"Amusement"* (words from *Boring* to *Amusing*) and *"Attractiveness"* (words from *Pleasant* to *Unpleasant*). Participants were also asked how much they felt certain emotions such as, *"Happiness"*, *"Surprise"* and *"Sadness"* while listening to the excerpts. Experiment I featured three melodies performed at different tempos (90, 120 and 150 BPM) and looked at emotional responses to the variation in tempo. Results showed that increasing tempo generated significantly higher scores for positive emotions such as *"Happiness"* and *"Surprise"* and greater scores on the *"Tension"* and *"Expressiveness"* scales while decreasing the perception of *"Sadness"* thus confirming the view that musical tempo variations impact emotions. Experiment II looked at how rhythmic variations impacted emotions. The experiment involved exposing participants to three variations of a musical pattern with different rhythmic structures. Results of the experiment showed that variations featuring shorter note values, this meaning shorter note duration such as sixteenth notes, led to higher scores in *"Happiness"* and *"Surprise"* emotions as well as in descriptive sales *"Tension"*, *"Expressiveness"* and *"Amusement"* compared to the original main rhythmic pattern. Therefore, this study showed that both tempo and rhythm have significant influence on consumers' emotions towards the music as faster tempos and shorter note value rhythmic patterns led to more positive emotional responses by listeners. Other relevant research conducted by Hevner (1936) on tempo and rhythm found that firmer rhythms were perceived as more serious whilst smoother rhythms were perceived as happier and, as noticed by Gundlach (1935), more brilliant or animated. Wedin (1972) further noticed that the expressiveness of the rhythmic interpretation also altered the way in which music was perceived. Explicitly, staccato-note-filled music was perceived as more energetic and lively, specifically when performed with great intensity compared to legato music which led to a more peaceful and tranquil mood.

2.2.2 Effects of changes in pitch

Bruner's (1990) research and analysis of academic findings on the impact of pitch on mood summarised that there is a strong relationship between pitch and perceived happiness where higher pitches are considered as happier whilst lower pitches are sadder. Hevner (1936) noticed that ascending melodies were considered as more dignified whereas descending melodies more serene. Furthermore, Gundlach (1935) found that music featuring greater note range extensions were perceived as more brilliant compared to those with smaller note range extensions considered as more mournful.

2.2.3 Effects of changes in volume

A study conducted by Gundlach (1935) on the effects of tempo and dynamics on the perception of emotion in music showed that the loudest musical excerpts used in his study were perceived as the most triumphant and/or animated whilst the softest excerpts were perceived as the most tranquil. This was further confirmed by research conducted by

Watson (1942) who found that songs perceived as happiest were, in fact, the loudest and songs perceived as peaceful were the softest.

2.2.4 Effects of changes in other variables

Bruner (1990) summarised results from other findings showing that musical repetition would result in altered perceptions of complexity consequently impacting affect when musical patterns would become predictable. Furthermore, Vinovich (1975) looked at the relationship between the information delivery and the background music finding that altering the musical moods would lead to an altered interpretation of the same video stimulus. Therefore, showing that viewers create an emotional prediction of the video stimulus that corresponds to the feelings induced by the musical mood.

2.3 Music features effects in retailing

The direct manipulation of specific musical features can be used to impact consumer behaviour in the field of retailing. For this reason, brands can use this knowledge to obtain and stimulate specific in-store consumer behaviour.

2.3.1 Changes in tempo

Various studies provide evidence that altering the tempo of the background music in a retail environment does impact consumer behaviour. Chebat et al. (2001) confirmed the views of Hecker (1984) supporting the idea that *"cognitive effects of music stem from its capacity to attract attention".* There is a threshold beyond which the music attracts attention to itself rather than the salesperson. Findings from Chebat et al. (2001) suggest that a slow tempo stimulates greater cognitive responses to the sales encounter. Unlike fast tempo, a slow tempo does not attract attention to itself therefore allowing greater (or at least unvaried) cognitive activity. Oakes et al. (2008) found that slower tempo music produced more positive effects than faster tempo music supporting their initial hypothesis that positive affective responses in terms of relaxation, satisfaction and positive disconfirmation of wait expectations would be enhanced with slower tempo music compared to faster tempo music. Furthermore, Eroglu et al. (2005) found that more people would avoid shopping at a store with faster tempo music. Caldwell et al. (1999) provide evidence that tempo also has an impact on the perception of time and money spent. The study, conducted at a restaurant, suggests that slower tempo music leads customers into spending a significantly greater amount of time compared to the amount of time they would spend in a place with faster tempo music. Regarding the impact on the amount of money spent, the study suggests that slower tempo also significantly affects the amount of money spent as customers spent greater amounts in restaurants with slower tempo music. These findings are also confirmed by Milliman (1986) who analysed the behaviour of restaurant customers when exposed to tempo manipulation of the background music and found that once the food was served, customers given the slower tempo music spent significantly more time completing their dinners and leaving compared to customers receiving the faster tempo music. Therefore, the increased time to complete a dinner and leave contributes to the evidence that a slower tempo results in a slower speed of locomotion. The study also showed that the estimated average gross margin per itemised statement was significantly greater for customers receiving slower tempo music, therefore, showing that customers receiving the slower tempo treatment would spend more money. Another study conducted by Milliman (1982) provides evidence that the pace of in-store traffic was significantly slower when consumers were exposed to slower tempo music compared to faster tempo music. Although not statistically significant, Milliman (1982) noticed that consumers exposed to slower tempo music were even slower than those exposed to no music. The study also provides evidence that customers exposed to slower tempo music generated significantly higher sales volumes compared to those exposed to faster tempo music. These results appear reasonable with the in-store traffic results as it is logical to believe that customers moving more slowly in the store are more inclined to make purchases and customers who move more quickly through the store tend to make less purchases. Another study by Roballey et al. (1985) found that the presence of background music in a cafeteria significantly increased the average number of bites per minute. When exposed to faster tempo music, subjects would take more bites per minute thus supporting the study's initial hypothesis that eating speed would increase with faster tempo music.

2.3.2 Changes in volume

Studies also suggest that variations in volume have an impact on consumer behaviour. Sullivan (2002) conducted an experiment in a restaurant analysing whether altering the volume of the background music (low volume against high volume) would impact the duration of the stay and its expenditure. Results suggest that with lower volume music, mean duration is significantly lower compared to the mean duration of consumers exposed to higher volume music. Furthermore, the study shows that the mean expenditure for consumers exposed to lower volume music was significantly greater than the mean expenditure for consumers exposed to higher volume music. Therefore, this study shows that volume of the background music significantly impacts duration and expenditure of consumers. Additionally, Biswas et al. (2019) analysed the effect of ambient music volume on food choices and sales. The study found that low volume music would induce consumers into a state of relaxation and consequently increase sales of healthy food whilst higher volume music would result in greater excitement levels and consequently leading to higher levels of unhealthy food sales. Garlin and Owen (2006) also found that lower volume background music in the retail environment leads to consumers having a more favourable view of the venue. Furthermore, a study conducted by Smith and Curnow (1966) in two supermarkets showed that, when exposed to louder volume music, consumers moved at a significantly faster speed compared to when exposed to softer music. Nevertheless, this did not significantly impact consumer satisfaction levels nor sales thus supporting a previously reported *"arousal hypothesis"* predicting that *"a certain level of noise will increase activity"*. Erkens (2014) also found that the volume of background music alters consumers' perception of wait time. The study investigated consumers' perceived waiting time while in line in a bakery and the results showed that respondents perceived their wait to be shorter when exposed to louder volume background music. Mandila and Gerogiannis (2012) reveal that volume impacts consumer satisfaction levels. In this study, customers at a coffee bar were asked whether they considered the music being played appropriate and the results showed that the most satisfied customers were those exposed to lower volumes.

2.3.3 Changes in mode

A study conducted by Husain et al. (2002) demonstrated the relationship between musical mode and mood. In fact, they found that participants exposed to a piece of music in major mode altered their mood in a positive direction compared to participants exposed to the same musical piece but manipulated in a minor mode whose mood was altered in a negative way. The study further suggests that, in accordance with prior research by Donovan and Rossiter (1982) on atmospherics and their positive correlation with mood and customer behaviour showing that pleasure and arousal are significant mediators of intended shopping behaviour within stores, music in a major mode could lead to greater sales compared to music in a minor mode. A study conducted by Kellaris and Kent (1992) provides evidence that musical mode also impacts listeners' temporal perceptions. The study shows that perceived duration was longest for subjects exposed to major mode music (positively valenced) compared to the perceived duration of those exposed to minor mode music (negatively valenced) whose perception was shorter. For this reason, consumers exposed to major mode music may overestimate the amount of time spent in a store whereas consumers exposed to minor mode music may underestimate the amount of time spent and, in accordance with Yalch and Spangenberg (2000) who found that subjective over and underestimation of time spent in a store affect actual time spent, lead to longer or shorter shopping experiences.

2.3.4 Relationship and effects of changes in tempo and mode

Some research also presents evidence of a relationship between the manipulation of tempo and mode together. In fact, Husain et al. (2002) the combination of major mode with faster tempo and minor mode with slower tempo resulted in greater enjoyment. In addition to this, Knoferle et al. (2012) found that, in agreement with the findings reported by Milliman (1982, 1986) regarding the impact of slow tempo on sales, the positive main effect of slow tempo strongly depends on the musical mode of the musical piece. In this study, only the combination of minor mode and slow tempo positively impacted sales.

2.4 Music features effects in advertising

From a broader perspective, as applies to retailing, direct manipulation of musical features in the field of advertising can also be used to stimulate specific consumer behaviour. Zander (2006) conducted a study on how music alters first impressions of brands and product endorsers and found that, participants exposed to the same endorser paired with different styles of music attributed different feelings, such as, level of exuberance, orderliness and diligence. Another study conducted by Oakes (2007) demonstrated that greater congruence between music and advertising increased communications effectiveness by "*enhancing purchase intent, recall facilitation, brand attitude and affective response*". Music aids communication, a study conducted by Hung (2001) looked at teaser ads and the use of nonverbal executional cues acting as verbal captions to aid communication. The study shows that interactive audiovisual images are a fundamental element of the meaning enactment process as the music connects and emphasises specific visual events with the aim to attract the consumer's attention.

2.4.1 Presence and likeability of music in commercial ads

A study conducted by Brooker and Wheatley (1994) explored the effects of music and the spokesperson of a radio advertisement on consumers' recall and cognitive responses. The research consisted in participants simulating a car drive and being exposed to a radio talk show featuring three commercial ads. For what regards the effects of music, Brooker and Wheatley presented two hypotheses, the first one believing that listeners exposed to an advertisement featuring a musical background would remember less of the advertising message compared to those exposed to the commercial advert without background music. Whilst the second hypothesis assumed that the likeability of the background music in an advertisement would impact cognitive responses. Specifically, the more the listener likes the background music, the greater the positive cognitive response. The greater the degree of dislike, the greater the negative cognitive response towards the advertisement. Results supported the first hypothesis predicting a negative impact on recall of the advertisement when listeners were exposed to background music whilst, regarding the second hypothesis, results showed that listeners who liked the musical background had a more positive cognitive response compared to listeners exposed to no music or were neutral towards the music, yet, the difference was not statistically significant as listeners exposed to no music at all had the same cognitive response to those exposed to music but had neutral feelings towards it. However, listeners exposed to background music they did not like had a statistically significant poorer cognitive response to the advertisement. Vermeulen and Beukeboom (2016) conducted a study exploring the effects of pairing background music to advertising on consumer choice further developing controversial research conducted by Gorn (1982). Vermeulen and Beukeboom (2016) conducted three conceptual replications of Gorn's (1982) experiments. Experiment I looked at the influence of music and product colour on consumer choice by exposing participants to a commercial video featuring background music and then asking them to select a phone cover. Participants could choose between two colours (dark blue and red) for the phone case, while two versions of the same song were used. Results showed that music significantly influenced the participants' phone cover choice by inducing participants into selecting the advertised phone cover when the background music was liked. Experiment II looked at whether the presence of background music and its effects extended to higher-involvement products such as bicycles. The experiment was structured in the same way as in experiment I using the same background music but differing the product (from phone cover to bicycle) and the colour of the bicycle (from dark blue and red to orange and green). On the other hand, compared to experiment I results were different as in experiment II, music did not have a statistically significant influence on bicycle choice. Experiment III used a two-factor design (liked versus disliked music) and looked at the influence of music liking on brands and their products' evaluations. The study used laptop sleeves and participants were asked to rate their attitudes towards the music, the brand, the product, the logo, the slogan and, finally, whether they would purchase the product. Results showed that liked music significantly impacted and improved both brand and product evaluations. Unlike findings reported by Gorn (1982), Vermeulen and Beukeboom's (2016) study supports that music effects were weaker and did not extend to the likes of higher-involvement products such as bicycles. Nevertheless, the study confirmed that music does influence consumers' product choice.

2.4.2 Presence and congruity of music in advertising

Alpert et al. (2005) analysed how background music influenced moods and emotions by studying the relationship between the evoked moods that are congruent versus incongruent with the purchase occasion and their impact on the final purchase intention. The study looked at two hypotheses, hypothesis I looked at whether background music considered to be "happier" impacted consumers' mood in a more positive way compared to background music considered to be "sadder". Whilst, on the other hand, hypothesis II looked at when the relationship between the evoked mood and the purchase occasion mood was congruent and whether this relationship had an impact on the purchase intention in a positive way compared to when the evoked mood was incongruent with the mood for the purchase occasion. The study involved exposing participants to certain product advertisements of which the studied ones featuring different types of background music ranging from “happy” to “sad” and different occasion scenarios (hospital against birthday). Participants were asked to express their attitudes, feelings, thoughts and purchase intentions towards the advertisement and product. Results showed that background music significantly impacted mood, however, it did not directly impact purchase intention as this was influenced by the occasion. A significant interaction between music and occasion was found, thus showing that the influence of music on consumers’ final purchase intention was different depending on the perceived mood for the occasion and, therefore, demonstrating that the congruence between music presence and the communicated occasion significantly influenced consumer behaviour.

2.4.3 Changes in mode

Musical mode can have a strong influence on consumers’ mood, for this reason, it can be used as a tool to aid communication in the field of advertising as a means to stimulate certain consumer behaviour and alter consumers’ perception of a brand or product. A study conducted by Stout et al. (1990) looked at how consumers reacted to different musical elements of advertisements presented as television commercials in malls. Results showed that musical mode was the most influential in terms of number of reactions. The study in fact concluded that using the major mode led to higher learning by consumers due to having greater behavioural intent toward and making greater personal connections with the ad whereas the minor mode led to greater irritation and were scored less favourably. Kellaris and Kent (1991) conducted research exploring the effects of tempo and modality on listeners’ responses to music and, for what regards the musical mode, found that modality had an influence on arousal and intent. More specifically, the use of atonal modalities produced the least positive results. Furthermore, according to Liu et al. (2022) the combination of subjective (such as music liking) and objective (music mode and music tempo) characteristics of music in advertisements impact the consumer’s final purchase intention. Although dependent on a subjective perception, the likeability of a musical piece can aid in the creation of positive brand attitudes, thus promoting consumer purchase intentions. The musical mode can further influence the effectiveness of this process and using major mode music in advertisements further boosts the beneficial effect of the positive brand attitudes on the consumer’s purchase intention. The study emphasises on the possibility of combining music likeability to musical mode to induce consumers into purchasing more of a brand's product.

2.4.4 Changes in tempo

As is the case with alterations of the musical mode, manipulation of musical tempo has also been studied as a mean to convey different meanings and stimulate consumer behaviour in the field of advertising. The previously mentioned study conducted by Kellaris and Kent (1991) looked at the effects of tempo and modality on consumer responses. The study featured two experiments, experiment I looked at the manipulation of tempo and mode by directly creating a musical piece whilst experiment II looked at the manipulation of tempo and mode by using commercially recorded music. For what regards tempo, results showed that tempo had positive main effects on the evaluation of the music's ability to generate arousal and behavioural intent further adding to a study conducted by Stout and Leckenby (1988) demonstrating that faster tempo led to a more positive evaluation of an advertisement.

2.4.5 Changes in the placement of the music

Hypothesis II of the previously mentioned study conducted by Brooker and Wheatley (1994) investigating the effects on consumers of background music and musical tempo in a radio advertisement looked at how the placement of music (music played at the start of the advertisement against music played as background) in an advertisement will influence recall, feelings, attitudes and purchase intention. Results showed that music placement in a radio ad significantly impacted the dependent variables. Advertisements featuring music as an introduction led to greater recall, purchase intentions, feelings of joy and positive attitudes towards the product compared to advertisements that featured background music.

2.5 Music features and digital music industry

Online streaming platforms have changed how present-day music is being distributed and consumed all over the world. Spotify is currently the most popular streaming platform in the world, and it comes with no surprise that its ability to create tailor-made playlists and song recommendations revolutionised the music consumption industry. Spotify's unique algorithm analyses songs and identifies different musical characteristics in order to categorise them.

2.5.1 Spotify's track audio features

Acousticness

Acousticness refers to the extent to which a track is considered acoustic. Values range from 0.0 to 1.0.

Danceability

Danceability refers to the extent to which a track is suitable for dancing. This reading is based on a combination of different musical elements including tempo, beat strength, rhythm stability and overall regularity. Values range between 0.0 and 1.0 where 0.0 represents least danceable and 1.0 represents most danceable.

Duration

Duration is the total duration of the track in milliseconds (ms).

Energy

Energy is a perceptual measure of the intensity and activity of a track. It is common for energetic tracks to also feel fast, loud and noisy. Values range from 0.0 to 1.0 where 0.0 represents low energy and 1.0 represents high energy.

Instrumentalness

Instrumentalness represents the degree to which a track contains no vocals. A track with no vocals will have a score of 1.0 whilst a track featuring vocals will have a score closer to 0.0. It is common for instrumental tracks to have a value above 0.5.

Key

The key refers to the key the track is in. Numerical values are assigned to different keys, for example, 0 = C, 1 = C#/D♭, 2 = D and so on. Values range from -1 to 11 where -1 = represents a song where the key was not detected.

Liveness

Liveness represents the degree of live audience present in the recording. Higher liveness scores will represent a higher likelihood of the track being performed in front of a live audience. Values above 0.8 represent strong probabilities that the song is live.

Loudness

Loudness represents the average of the overall loudness of a track expressed in decibels (dB). Loudness can be perceived as a reading of physical strength (amplitude) of a track. Values typically are between -60 and 0 db.

Mode

Mode refers to the modality (major or minor) of the song where major is represented by a value of 1 and minor by a value of 0.

Speechiness

Speechiness indicates the presence of spoken words in a song. The higher the similarity to speech-like activity (for example a podcast), the closer the value to 1.0. Values above 0.66 typically describe tracks entirely made of spoken words whilst track with scores between 0.33 and 0.66 may contain both music and speech. Values below 0.33 typically represent music/non-speech-like tracks.

Tempo

Tempo indicates the overall speed of a song expressed in beats per minute (BPM).

Time signature

Time signature provides an estimate of how many beats are in a musical measure. Values range between 3 and 7 indicating the number of beats in a bar, for example, 3 = 3/4.

Valence

Valence indicates the degree of positiveness of the song with higher valence scores indicating the track is more positive/happier while tracks with lower scores indicate negative/sadder tracks. Values range between 0.0 and 1.0.

2.5.2 *Effects of Spotify's track audio features*

A study conducted by Nijkamp (2018) explored the effects of Spotify's audio features on song popularity (expressed in number of streams). Nijkamp (2018) constructed the experiment by retrieving data for one thousand songs from ten genres from Spotify's API (Application Programming Interface). Results showed that *Acousticness, Duration, Instrumentalness* and *Liveness* were all negatively related to a higher stream count, thus confirming Nijkamp's initial hypotheses. *Danceability* was positively related to a higher stream, thus confirming Nijkamp's initial hypothesis. On the other hand, *Energy* was found to be negatively related to a higher stream count, thus disagreeing with the initial hypothesis of *Energy* being positively related to higher stream count. Results also showed that there were no significant relations among the *Keys* of C, G and E and higher stream count. On the contrary, significant results were found for the *Keys* of D and B. *Loudness* was also not found to be positively related to higher stream counts and so was the case for *Valence*. The initial hypothesis of the *Major mode* being positively related to a higher stream count was also rejected and found to be negative instead. The hypothesis for *Speechiness* was also rejected as the relationship was found to be positively related rather negatively related as hypothesised. Finally, the hypothesis for *Tempo* was accepted as *Tempo* was not related to stream count. Nevertheless, Nijkamp (2018) argues that although results show elements of significance for certain relationships, these were generally weak. Additionally, a regression model looking at the model's explanatory power presented a value of 20.2% meaning that the model explains 20.2% of the stream count variation, therefore showing that the model is not effective in explaining stream count by itself. On the other hand, a study conducted by Saragih (2023) investigated how Spotify's audio features impact song popularity in Indonesia by using classification and regression models. According to the study, longer *Duration* songs were more popular, alongside this, higher *Valence* and *Danceability* also contributed to greater popularity. Whilst, on the contrary, lower *Speechiness* was associated to increased popularity. Although this research only focuses on the Indonesian market, there appears to be some disagreement with findings from Nijkamp (2018). In fact, little research can be found studying the effects of Spotify's audio features on song popularity.

Chapter 3: Spotify's algorithm and music features

3.1 Spotify and its functions

3.1.1 Spotify introduction

Spotify is a Swedish music streaming platform launched in 2008. As of February 2024 (Spotify; About Spotify, 2024), Spotify is currently the largest music streaming platform featuring over 100 million songs, 5 million podcast titles and 350,000 audiobooks. Spotify offers two versions of the app, premium and free. The app has over 602 million active users of which 236 million (premium) paying subscribers and is currently available in over 180 markets. The app features many unique functions including the possibility for users to browse songs/podcasts/audiobooks based on the app's recommendations, the user's mood, the *Discover weekly* function, the *Radio* function and the *Fans also like* function.

3.1.2 "Search" function

The *Discover Weekly* function is an algorithmic playlist focused on providing users with music/artists they have never heard of. The selection of music is the result of algorithmic analysis of the user's preferences generating similar recommendations based on the user's present preferences.

3.1.3 "Radio" function

The *Radio* function is an algorithmic playlist for users created specifically around a specific track or artist. When listening to a track/artist, Spotify will suggest the *Radio* channel for that track/artist featuring a playlist made up of many other tracks considered similar to that specific track/artist.

3.1.4 Daily mixes

The *Daily Mixes* are a set of algorithmic playlists specifically created for a user and updated every day. *Daily Mixes* can reach a total of six different playlists each focusing on different styles and genres to cope with users' diverse musical tastes. For example, a user who enjoys smooth jazz music to study but also enjoys electronic dance music (EDM) when working out would receive two diverse *Daily Mixes* where *Daily Mix 1* would present a selection of smooth jazz music to study to whilst *Daily Mix 2* a selection of electronic dance music hits to work out to.

3.1.5 "Release radar" function

The *Release radar* is a playlist created by Spotify that updates every Friday featuring new songs by the user's favourite artists and other artists Spotify think they will like. The intent of this feature is to help users remain informed regarding their favourite artist's new releases.

3.1.6 "Discover weekly" function

The *Discover Weekly* function is an algorithmic playlist focused on providing users with music/artists they have never heard of. The selection of music is the result of algorithmic analysis of the user's preferences generating similar recommendations based off the user's present preferences. According to Thingstad (2023), the scope of this function is to provide users with suggestions of music/artists they will likely enjoy but would not have discovered without the playlist.

3.1.7 "Fans also like" function

The *Fans also like* function is for when a user visits an artist's page or is listening to an artist, Spotify will recommend other similar artists based off data from other users who share similar musical taste and who also listened to that same artist. They will track what other artists those users have listened to and recommend them as similar artists.

3.1.8 Automatic playlist continuation

The *automatic playlist continuation* function focuses on providing an adequate continuation to a user's playlist. For example, this occurs when a user is listening to an album/playlist and reaches the last song. After the last song, Spotify will continue playing songs similar to those of the album/playlist without causing an interruption of the listening experience. Another example could involve a user listening to a song and creating a queue of songs to follow, once the queue ends, Spotify will continue adding similar songs to the queue.

3.1.9 Spotify blend

Spotify blend is a new feature recently added to Spotify. It is a shared algorithmic playlist that updates every day. *Spotify blend* allows users to create a *blend* playlist with their friends (as of today, up to a maximum of ten people). Spotify will add songs based off each member's listening activity blending common musical tastes and styles.

3.1.10 "On repeat" function

The *on repeat* function is an algorithmic playlist featuring songs users have been listening to many times in the last period.

3.1.11 Spotify wrapped

The *Spotify wrapped* feature is a creative tool used by Spotify to summarise to users their listening habits over the year. The *Spotify wrapped* is published towards the end of the year and features statistics regarding a user's listening habits. In addition to this, the *Spotify wrapped* includes a playlist featuring songs the user has listened to the most in that year.

3.2 The Spotify algorithm

3.2.1 The BaRT algorithm

The Spotify algorithm (referred to as the BaRT algorithm – Bandits for Recommendations as Treatments) is an advanced tool used to analyse consumers' musical preferences with the aim to provide personalised musical recommendations to Spotify users and enhance the user experience. What sets Spotify apart from its competitors is its ability to create custom playlists and song recommendations based on users' interactions with the app. Thus, meaning that the algorithm learns from a user's experience with the music on the app, whether the user listens to a song more than once or adds it to a playlist or whether they skip it. The algorithm processes the data and recommends music which is in line with the user's preferences. For the algorithm to be able to recommend music to a user based on the user's preferences, it needs some sort of categorisation of musical elements that make up a musical piece. These being referred to as Spotify track audio features (mentioned in the previous Chapter).

3.2.2 User search history

Spotify analyses what users search for when browsing for music using this data as an indicator of the user's musical preferences. This information is used and processed to improve algorithmic recommendations. Examples include users searching for Blues artists, Spotify will consequently recommend similar Blues artists and playlists.

3.2.3 Listening activity

Spotify will analyse a user's listening activity and use this as an indication of user preferences. This includes the genres of music a user prefers, what type of music they will listen to at different times of the day, what songs they skip, what artists they keep listening to and other user interactions with the music.

3.2.4 Playlist creation and interaction

Spotify will also analyse what playlists users listen to and save for further listening, what moods and genres they present and what music and genres they select when personally creating playlists. They use this data and compare it to other user playlists with the aim to improve and fine tune playlist song recommendations.

3.3 How the recommendation algorithm works

3.3.1 AI and machine learning

At the core of Spotify's recommendation system is a machine learning model developed and implemented in a way to achieve the company's desired objectives. In fact, in 2014, Spotify acquired *"The Echo Nest"*, a music intelligence and data platform. *"The Echo Nest"* combines machine learning and natural learning processing in order to analyse music and user behaviour. Through the processing of data and algorithms, machine learning enables AI (artificial intelligence) to develop human-like learning abilities which slowly become more accurate over time (*What Is Machine Learning (ML)? | IBM*, n.d.).
For this recommendation system to work, machine learning models and algorithms are used to generate user representations and item representations. There are two components that compose track representations. These are, ***Content-based filtering*** and ***Collaborative filtering***. ***Content-based filtering*** refers to the description of the track through examination of the content itself. ***Collaborative filtering*** refers to the description of the

track with reference to its connection with other tracks present on the platform by analysing user-generated assets. For the system to provide cohesive recommendations, it requires both ***Content-based filtering*** and ***Collaborative filtering*** to effectively create a bigger picture of the content on the platform.

3.3.2 Collaborative filtering

Collaborative filtering is a process that uses user behaviour to recommend music to other users with similar tastes. The process behind this technique makes reference to logic, if user X likes tracks A, B and C whilst user Y also likes tracks A and B but never heard of track C, then the algorithm will recommend user Y track C. Collaborative filtering occurs through a process of matrix manipulation, it clusters users that share similar musical taste (referred to as *user-user collaborative filtering*). Similarly, if many users appreciate the same items (such as songs) the algorithm will cluster them together considering them as similar items (referred to as *item-item collaborative filtering*). Collaborative filtering technique is widely used, examples include Netflix's "*You may also like*" and Amazon's "*Customers who bought this item also bought*". Figure 4 (Arya, 2023) provides a visual demonstration of collaborative filtering.

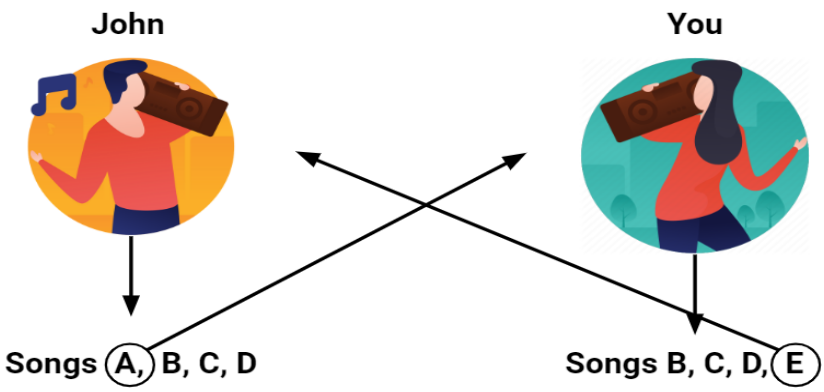


Figure 4: Visual depiction of collaborative filtering (Arya, 2023)

3.3.3 Content-based filtering

Content-based filtering can be divided in different steps. Firstly, Spotify analyses **artist-sourced metadata**. Once an artist (through its distributor) provides Spotify with the audio file of the track, an algorithm will study and process its metadata. Track metadata include (Pastukhov, 2022):

- *Track title*
- *Release title*
- *Artist name*
- *Featured artists*
- *Songwriter credits*
- *Producer credits*
- *Record label*
- *Release date*
- *Genre and sub-genre tags*
- *Music culture tags*
- *Mood tags*
- *Style tags*
- *Primary language*
- *Instruments used*
- *Track typology*
- *Artist hometown/local market*

The next step involves the **processing of raw audio signals** and integration of the audio features. Although ***collaborative filtering*** represents an effective technique to recommend items to users, situations may arise where new songs are uploaded to the platform but fail to get recommended due to lack of available data to effectively analyse the songs and its similarities with other songs (referred to as the "cold start problem"). Another "cold start" situation refers to new users signing up to the app and lacking sufficient listening time to provide the system with data that can be analysed, thus, causing an inability to establish user preferences and music recommendations. For this reason, Spotify analyses raw audio through **convolutional neural networks (CNN)**. Convolutional neural networks are a type of deep learning algorithms used to analyse visual (and audio) data. This process works by converting an audio file into a spectrogram (visual representation of a signal as it varies over time). Figure 5 represents a depiction of a spectrogram (Sinha, 2021).

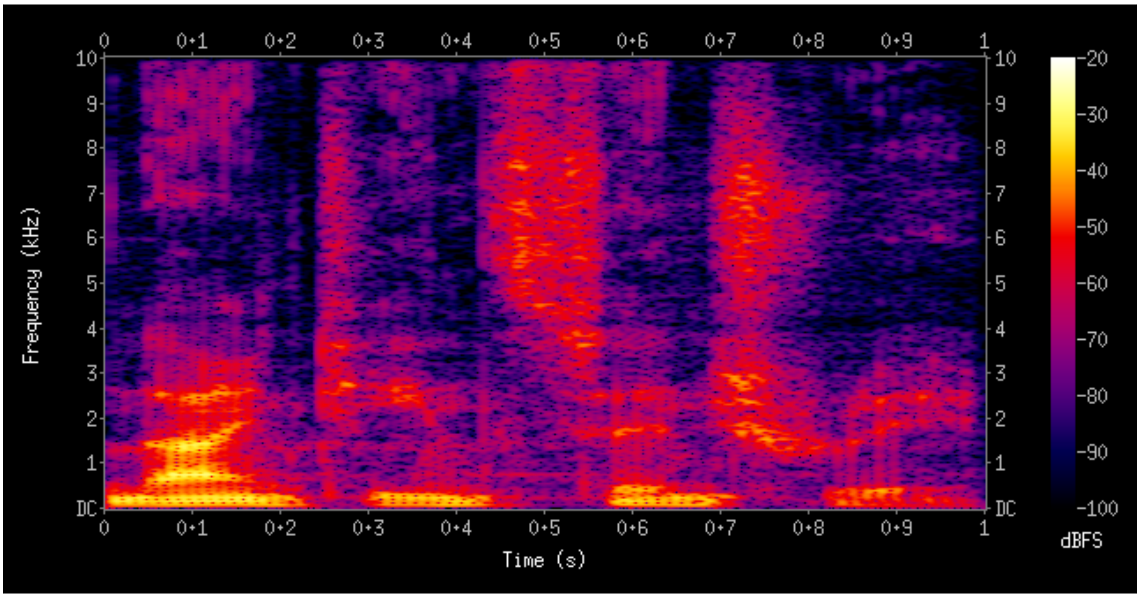


Figure 5: Spectrogram (Sinha, 2021)

This allows Spotify to analyse and compare songs based on the musical characteristics (such as BPM, key, tonality, pitch and others) of each audio file without a song having reached significant popularity among users. Additionally, another algorithm focuses on the analysis of a track's temporal structure and dividing the audio into separate segments as depicted in Figure 6 (Pastukhov, 2022).

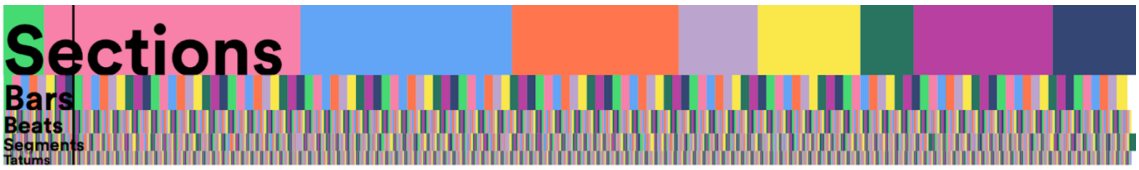


Figure 6: Depiction of a temporal audio analysis for the song: "Industry Baby" by Lil Nas X (feat. Jack Harlow). (Pastukhov, 2022)

Following the processing of raw audio signals, the next step features the **analysis of text with natural language processing models** with the objective of obtaining information describing the track and the artist. This process applies to three situations, the first one being ***analysis of the lyrics***. This function looks at the meaning and the main topics behind the lyrics of a song while also looking out for other information such as names of brands, locations and names of people. Following the analysis of the lyrics, there's an analysis of

web-crawled data where the models scan the web for already-existing descriptions of the song/artist. Finally, the next algorithm looks *at* ***user-generated playlists***. The algorithm looks at all the user-generated playlists that include the track with the aim to gather more information regarding the track's genre, style and mood.

3.4 The long tail problem

The long tail problem refers to a common situation in music recommendation systems. The long tail problem refers to the situation where less popular songs/artists with fewer streams struggle to get recommended, nevertheless, due to there being an incredibly vast amount of smaller, less popular songs/artists, altogether these actually account for a greater aggregate number of streams compared to all the more popular "hit" songs present on the market. Figure 7 (Owsinski, 2019) provides a visual depiction of the long tail problem.

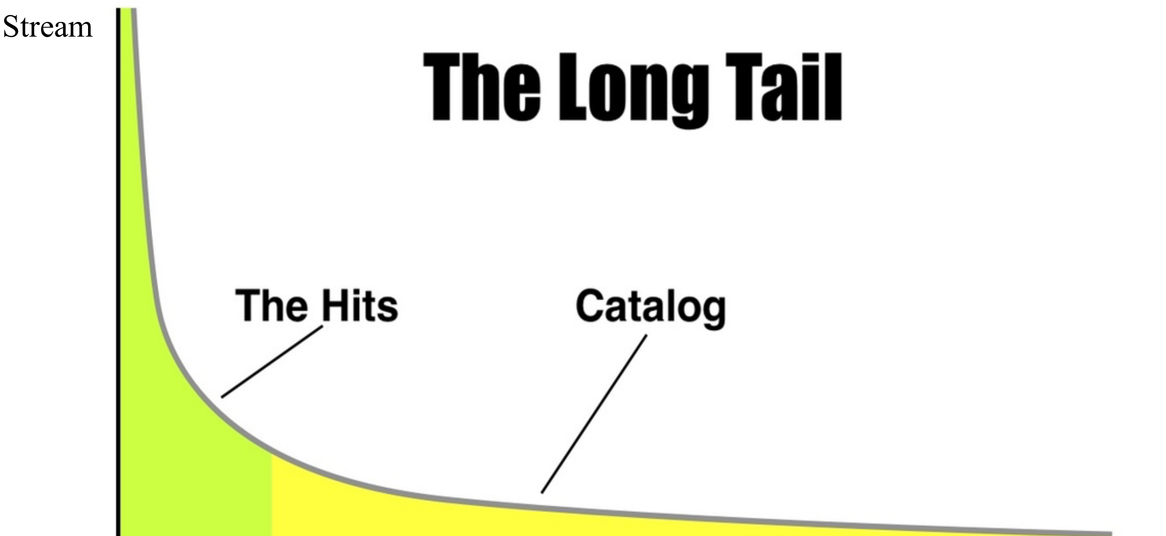


Figure 7: Visual depiction of the long tail problem. (Owinski, 2019)

As shown in Figure 7 above, the Y-axis represents the number of streams for a song/artist whilst the X-axis represents the songs/artists. The light green area shows the smaller yet more popular group of songs/artists, representing the niche of artists and songs that generate most of the industry's revenues, are more known and, consequently, are more recommended to users. The yellow area shows the “long tail” of less known songs/artists with few streams that consequently are less recommended by recommendation systems.

Chapter 4: Experimental research

4.1 Theoretical background

Music has always been highly connected to humans and their emotions, in fact, it can play a major role in influencing a person's mood. For this reason, over the years, it has become a common practice to integrate musical stimuli in the field of marketing. Globalisation and saturated markets make the task of branding highly complex and of fundamental importance. A company's ability to create a strong, consistent brand identity involves working with many different elements, including music. There are different factors that can alter the perception of a musical stimuli, and, for this reason, when managing a brand and trying to build a recognisable identity, organisations need to be aware of the different features of a musical stimulus that can be altered and how these will impact consumers in order to effectively strengthen their brand identity. Furthermore, when it comes to the fashion industry, the concept of branding for luxury and fast fashion brands becomes increasingly relevant due to the highly competitive nature of the industry.

Nevertheless, while the previous chapters looked at the concepts and characteristics of musical stimuli manipulation in marketing, this chapter will focus on the experiment of this research. Firstly, by describing the methodology and design of the study, then, by summarising the results.

4.1.1 Literature review

Using a study conducted by Bruner (1990), "Music, mood, and Marketing" as the main source of inspiration for this research, alongside other research looking at the effects of musical characteristics manipulation on consumers, few updated literature specifically addresses the effects of music manipulation in the fashion industry. Musical tempo is one fundamental component of music, with differences significantly impacting mood. In fact, studies such as Levitin et al., (2018), have demonstrated that musical tempo has a direct effect on mood, noticing that slower tempos generally lead to a sadder mood, whereas faster tempos generally lead to a happier mood. This becomes relevant when looking at the findings mentioned in the previous chapters by Milliman (1982) providing evidence that musical tempo affects consumers' in-store pace, or findings from a study conducted by Caldwell et al. (1999) providing evidence that musical tempo manipulation impacts consumers' perception of time and money spent. Additionally, Eroglu et al. (2005) found that people avoided shopping in stores with faster-paced music. This further agrees with findings by Milliman (1982) proving that customers exposed to slower-paced music generated higher sales compared to customers exposed to faster-paced music. For this reason, although there are various musical characteristics that can be manipulated and studied, these topics suggest a possible area of study when looking at luxury and fast fashion brands and how these can use musical tempo manipulation to their advantage. Another study conducted by Doucé et al., (2022) looked at the congruence between background music and online stores finding that greater congruence leads to positive consumer responses. Additionally, a study conducted by Kim et al., (2023) looked at the moderating role of type of fashion brand (whether sports or luxury) on the effect of background music speed on consumers. Results suggested slower tempos were best associated to luxury brands and faster tempos were best associated with sports brands.

Consequently, this experiment will look at how *musical tempo variations* (whether **slow** or **fast**) may have a significant effect on *consumers' attitudes* (measured by four main dependent variables: ***brand liking***; ***willingness to visit the Instagram page***; ***willingness to pay for a belt*** and ***willingness to pay for a scarf***) and whether the *fit between the background music and the type of brand* will have a mediating effect on this relationship. Finally, the study will look at whether the type of brand (**luxury** or **fast fashion**) will have a significant moderating effect.

As a result, the following research hypotheses have been raised.

H1: Variations in musical tempo have a significant effect on consumers' attitude towards a brand. Specifically, slower musical tempos are more effective than faster musical tempos.

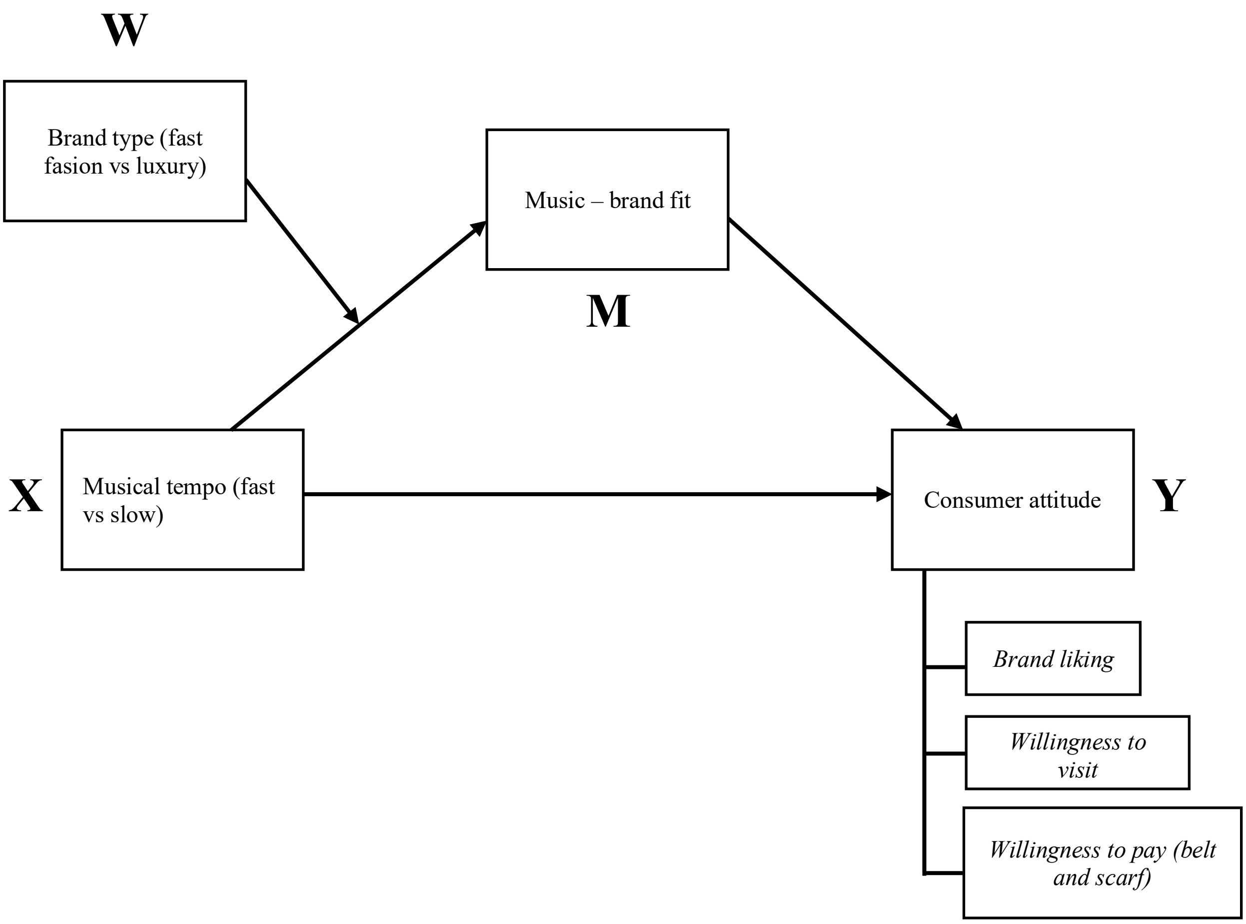
H2: The fit between the background music and the type of brand mediates the relationship between the musical tempo and consumers' attitudes. Specifically, musical tempo will influence the music – brand fit.

H3: The fit between the background music and the type of brand mediates the relationship between the musical tempo and consumers' attitudes. Specifically, a greater fit will positively impact consumer attitudes towards a brand.

H4: The type of brand moderates the relationship between the background music and the fit between the background music and the type of brand. Specifically, the type of brand will impact the relationship between the background music and the music – brand fit.

For this reason, this experimental study aims to explore the following research question:

"The influence of musical tempo variation on consumers' attitudes: the moderating role of the type of brand"



4.2 Methodology

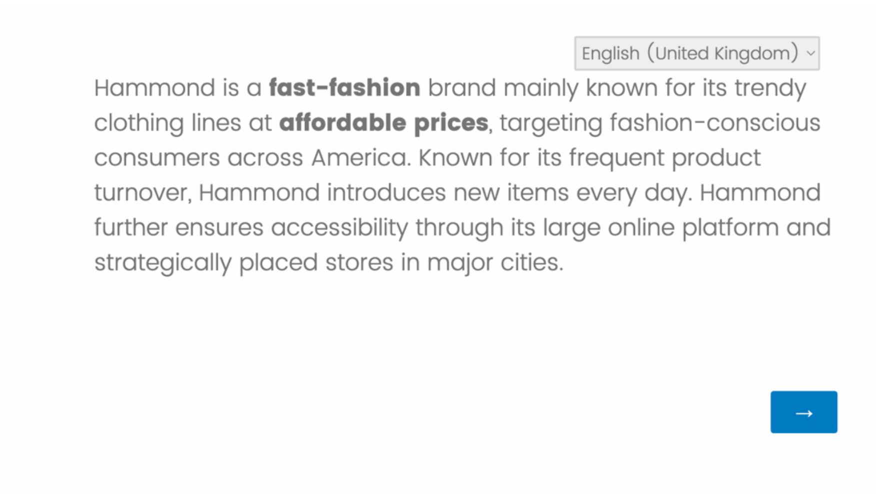
This experimental study is a 2x2 between-subjects causal conclusive research design. Results for the experiment stem from the responses to a questionnaire obtained through a self-administered survey conducted on the platform Qualtrics XM in Italy during the month of May 2024. Survey participants have been selected through a convenience sample. This sampling technique is known for its advantageous conditions such as the availability and ease of access to the target population at no economic cost. Demographic variables were not considered to influence results in a statistically significant way, for this reason, keeping in mind the target sample, results by male and female respondents of all ages have been included.

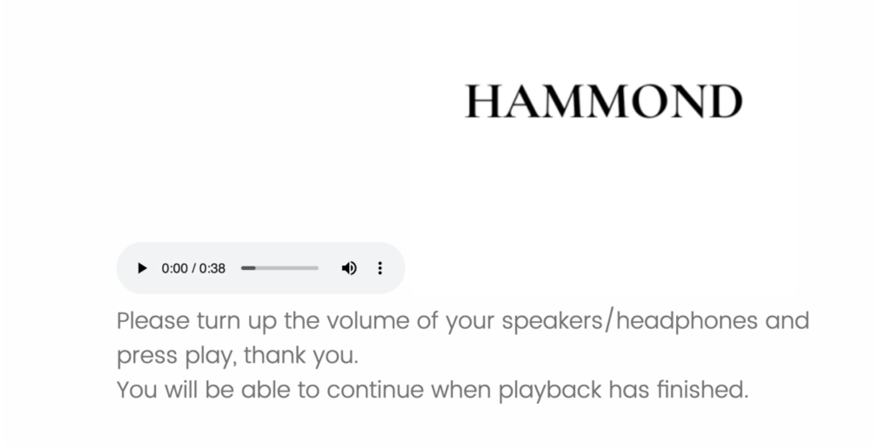
4.2.1 Description of the stimuli

Participants were exposed to a questionnaire featuring 13 questions of which 1 audio test, 10 specific and 2 demographics. As this study is a 2x2 research design, 4 different audiovisual stimuli have been created in order to manipulate the independent variable (musical tempo: **slow tempo** versus **fast tempo**) and the moderator (brand type: **luxury** versus **fast fashion**).

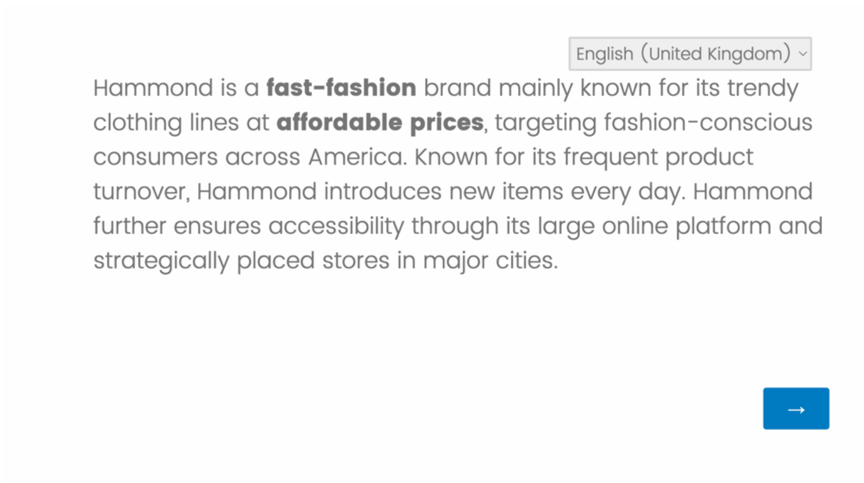
It is important to note that, for the purpose of this study, a fictitious brand called "Hammond" was used in all scenarios with the aim to avoid potential cognitive bias or biases related to brand sentiment. For this reason, the brand logo was created with Canva. Additionally, the brand logo is always the same and the composition of the background music (which was solely created for the purpose of this study on the Digital Audio Workstation - DAW, Logic Pro) is exactly the same for all scenarios differing only in terms of musical tempo.

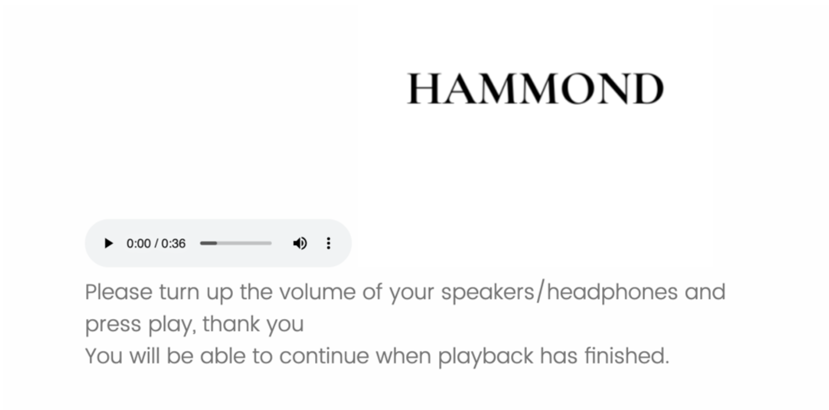
The first scenario featured a description of the fictitious **fast fashion** brand "Hammond" featuring background music with a **slow tempo** (95 BPM).



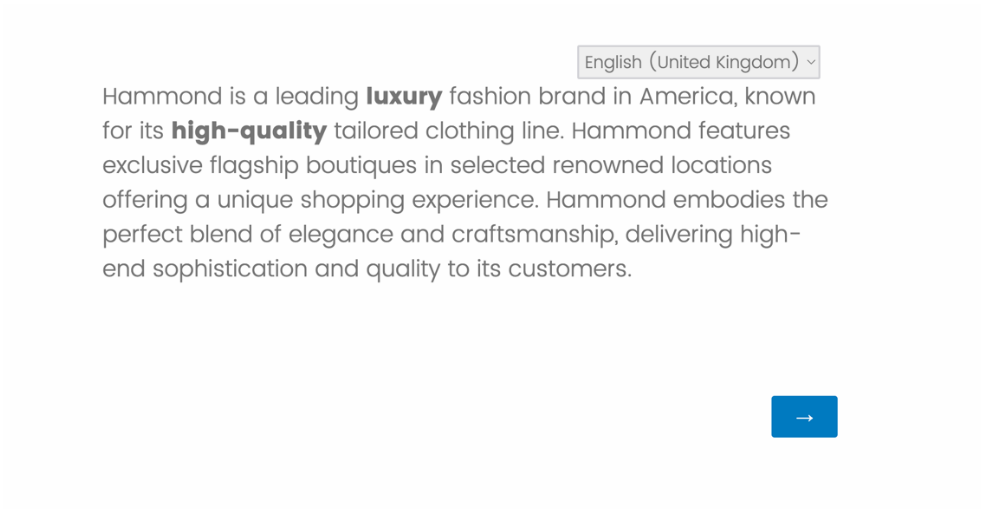


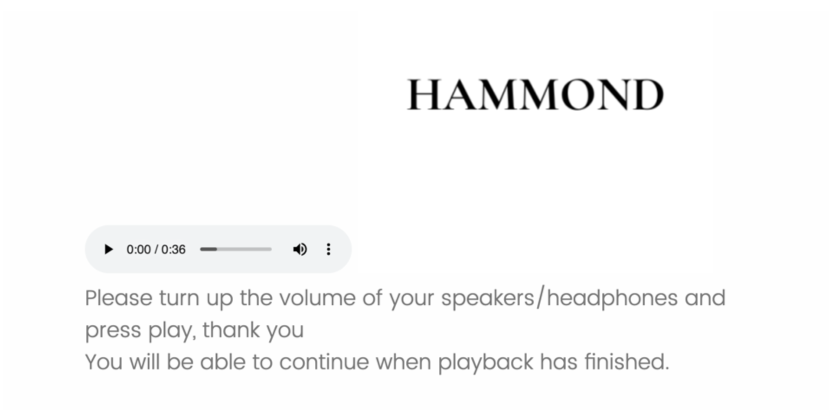
The second scenario featured a description of the fictitious **fast fashion** brand "Hammond" featuring background music with a **fast tempo** (120 BPM).



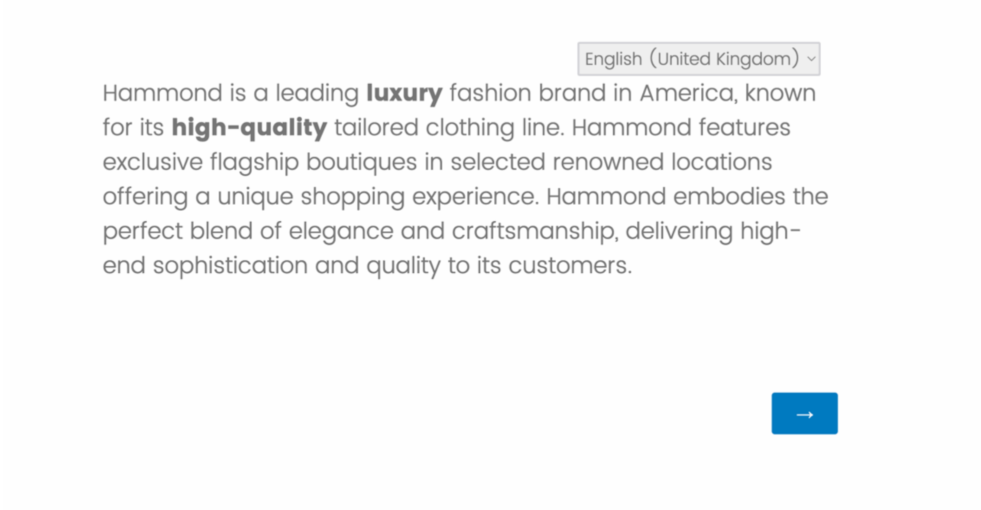


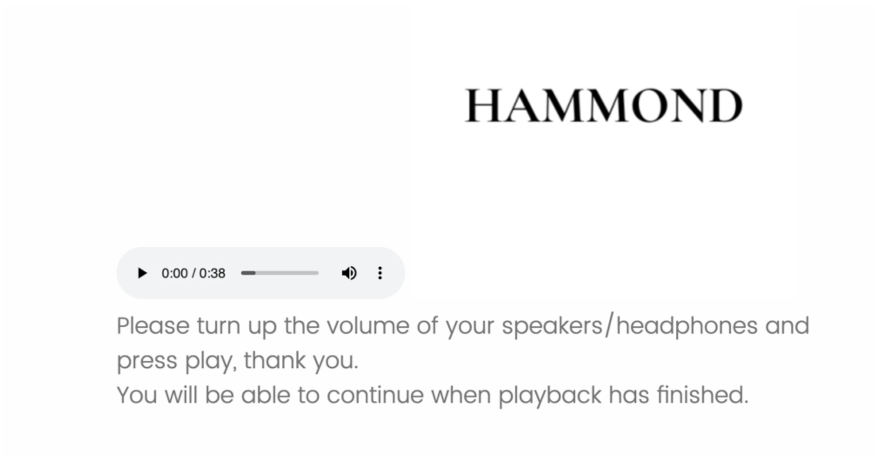
The third scenario featured a description of the fictitious **luxury** brand “Hammond” featuring background music with a **fast tempo** (120 BPM).





The second scenario featured a description of the fictitious **luxury** brand "Hammond" featuring background music with a **slow tempo** (95 BPM).





The questionnaire was divided in four main parts.

At the start of the questionnaire, participants were greeted with a small introduction featuring an explanation of the academic purpose of the experimental study. Furthermore, after mentioning the name of the university, participants were informed of the anonymity of the survey and information regarding the privacy of the data collection. Participants were then introduced to an audio check question asking to select a word mentioned in the audio file.

The second part of the survey featured a randomised block made up of four different scenarios. The randomisation process in the questionnaire played a fundamental role in order to expose participants uniformly to all the stimuli.

The third part of the survey was exposed to participants once they were shown one of the four scenarios. This block featured 10 questions: 4 questions regarding the dependent variables (brand liking, willingness to visit the Instagram page and the willingness to pay for the belt and scarf); 3 questions regarding the mediator *fit between the background music and the type of brand* and 3 questions regarding manipulation checks.
Besides the two questions on the willingness to pay for the belt and willingness to pay for the scarf which required a number entry, all other questions were validated by a 7-point Likert scale.
The first scale related to the dependent variable **brand liking** derives from the pre-validated scale Mitchell, A. A., & Olson, J. C. (1981). Are product attribute beliefs the only mediator of advertising effects on brand attitude?. *Journal of marketing research*, *18*(3), 318-332.
The second scale related to the dependent variable **willingness to visit the Instagram page** derives from the pre-validated scale Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision support systems*, *44*(2), 544-564.
The third scale related to the mediator **fit** derives from the pre-validated scale from Ahluwalia, R., & Gürhan-Canli, Z. (2000). The effects of extensions on the family brand name: An accessibility-diagnosticity perspective. *Journal of consumer research*, *27*(3), 371-381.
All scales have been readjusted to fulfil the needs of this experimental study.

The fourth part of the survey displayed the block featuring demographic questions where participants were asked their gender and age.

4.3 Results

4.3.1 Participants and sampling procedure

The survey was distributed to 244 individuals of which 197 respondents took part in a complete and exhaustive way. The remaining 47 incomplete responses were initially accepted and subsequently removed from the dataset. Respondents were given access to the survey through an anonymous link provided by the online platform Qualtrics XM, the link was then forwarded via messaging techniques and social media networks such as WhatsApp, Instagram and e-mail. The target sample mainly included university students, graduate students, newly hired employees and experienced workers located in Italy. For this reason, the average age of respondents was 28.68 years of age. Nevertheless, the age difference ranged from a minimum of 18 years to a maximum of 64 years of age.

Frequencies

Statistics

What is your Gender?

N	Valid	197
	Missing	0
Mode		2

What is your Gender?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	88	44.7	44.7	44.7
	Female	108	54.8	54.8	99.5
	Prefer not to say	1	.5	.5	100.0
	Total	197	100.0	100.0	

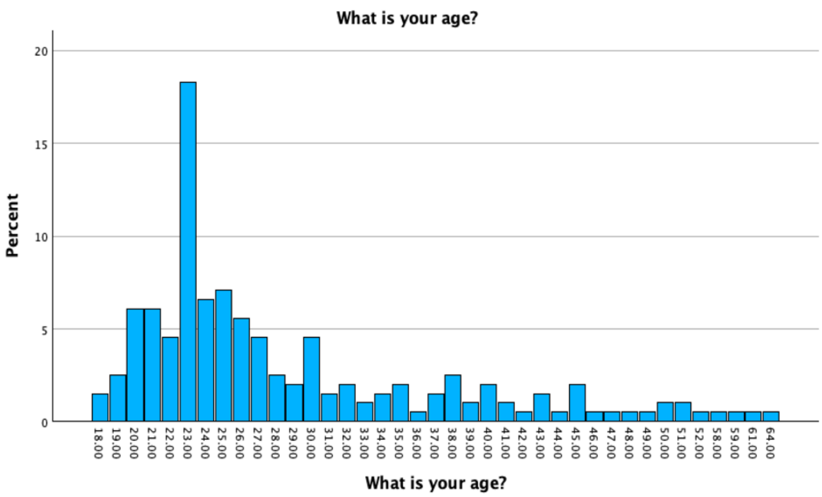
For what regards the gender of participants, results showed that the female gender prevailed representing 54.8% (108/197) of all respondents, the male gender represented 44.7% (88/197) of all respondents. The remaining 0.5% (1/197) of respondents preferred not to identify in a specific gender whilst no respondents selected the third gender/nonbinary option.

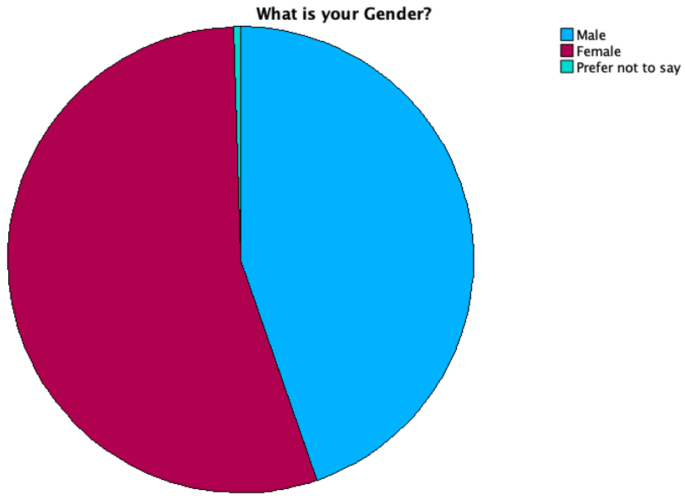
Frequencies

Statistics

What is your age?

N	Valid	197
	Missing	0
Mean		28.6853
Median		25.0000
Mode		23.00
Std. Deviation		9.22632
Variance		85.125
Range		46.00
Minimum		18.00
Maximum		64.00





4.3.2 Data analysis

All data collected through the questionnaire generated by Qualtrics XM has been exported to the statistical software SPSS (Statistical Package For Social Science) in order to proceed with the analysis.

An initial explorative Factor Analysis was conducted with the aim to examine and validate all items used in the conceptual model of this study. A Principal Component Analysis was used as Extraction Method utilising Varimax as rotation technique. In order to select the number of factors to extract, the Total Variance Explained table was used. Thus, verifying that, according to Kaiser's rule, the Eigenvalues were greater than 1 and that the cumulative variance percentage was greater than 60%. Additionally, both the Communalities table and Components Matrix were observed and all items had an extraction value greater than 0.5 and a loading score greater than 0.3. For this reason, all items composing the scales were kept and, thus, validated.

A Reliability test was then conducted in order to test the reliability of the scales used. The value for Cronbach's alpha was used assuring that the value was greater than 60%. For what regards the mediator, results provided a value of 0.969. Regarding the scales used for the dependent variables, as all were composed by only one item, no Factor analysis or Reliability test was deemed necessary.

Variable scale	KMO test	Bartlett test	Cronbach's Alpha
Fit between background music and type of brand	0.764	p-value = 0.001 < α = 0.05	0.969

Matrix 1

Outcome variable: brand liking

Model	coefficient	se	t	p
Constant	5.7451	0.2133	26.9378	0.0000
Musical tempo	-1.0651	0.3031	-3.5138	0.0006
Brand type	-0.8493	0.3063	-2.7727	0.0061
Interaction	1.0026	0.4342	2.3090	0.0220

A regression analysis was conducted using model 1 of the SPSS Process Macro extension Version 4.2 by Andrew F.Hayes. The independent variable X (musical tempo: slow versus fast) is of categorical nominal nature and, consequently, coded in two different conditions, where 0 (slow tempo) and 1 (fast tempo). The moderator W (brand type: luxury versus fast fashion) is also of categorical nominal nature and, therefore, coded in two different conditions, where 0 (luxury brand) and 1 (fast fashion brand). On the other hand, the first dependent variable Y1 (brand liking) is of continuous metric nature. From the table above it can be seen that musical tempo has a negative and significant effect with a regression coefficient β equal to a value of -1.0651 and a p-value equal to 0.0006. The type of brand also has a negative and significant effect with a regression coefficient β equal to a value of -0.8493 and a p-value equal to 0.0061. The interaction between the independent variable (musical tempo) and the moderator (brand type) is significant, with a p-value equal to 0.0220.

Conditional effects of the focal predictor at values of the moderator

Type of brand	effect	se	t	p
0.0000	-1.0651	0.3031	-3.5138	0.0006
1.0000	-0.0625	0.3109	-0.2010	0.8409

Looking at the conditional effects of the focal predictor at values of the moderator, it can be interpreted that when the type of brand is **luxury** (luxury = 0), increasing musical tempo (from slow to fast) has a negative and significant effect on the first dependent variable (brand liking). Where the regression coefficient β is equal to a value of -1.0651 and a p-value equal to 0.0006. Whereas, when the type of brand is **fast fashion** (fast fashion = 1), the effect of moving from a slow tempo to a faster tempo is not significant (p-value = 0.8409). For this reason, results suggest that fast fashion brands are free to choose whether to use slow or fast tempo music, whereas it makes sense for luxury brands to adopt a slower tempo musical background.

Matrix 2

Outcome variable: willingness to visit Instagram page

Model	coefficient	se	t	p
Constant	5.6863	0.2185	26.0275	0.0000
Musical tempo	-0.7663	0.3105	-2.4678	0.0145
Brand type	-0.5196	0.3138	-1.6561	0.0993
Interaction	0.4954	0.4448	1.1139	0.2667

A regression analysis was conducted using model 1 of the SPSS Process Macro extension Version 4.2 by Andrew F.Hayes. The independent variable X (musical tempo: slow versus fast) is of categorical nominal nature and, consequently, coded in two different conditions, where 0 (slow tempo) and 1 (fast tempo). The moderator W (brand type: luxury versus fast fashion) is also of categorical nominal nature and, therefore, coded in two different conditions, where 0 (luxury brand) and 1 (fast fashion brand). On the other hand, the second dependent variable Y2 (willingness to visit the Instagram page) is of continuous metric nature. From the table above it can be seen that there is no interaction (p-value equal to 0.2667) between musical tempo and type of brand. For this reason, there is no effect.

Matrix 3

Outcome variable: Willingness to pay for a belt

Model	coefficient	se	t	p
Constant	58.7843	4.5468	12.9287	0.0000
Musical tempo	-39.4043	6.4622	-6.0976	0.0000
Brand type	-20.9093	6.5299	-3.2021	0.0016
Interaction	17.2585	9.2570	1.8644	0.0638

A regression analysis was conducted using model 1 of the SPSS Process Macro extension Version 4.2 by Andrew F.Hayes. The independent variable X (musical tempo: slow versus fast) is of categorical nominal nature and, consequently, coded in two different conditions, where 0 (slow tempo) and 1 (fast tempo). The moderator W (brand type: luxury versus fast fashion) is also of categorical nominal nature and, therefore, coded in two different conditions, where 0 (luxury brand) and 1 (fast fashion brand). On the other hand, the third dependent variable Y3 (willingness to pay for a belt) is of continuous metric nature. From the table above it can be seen that musical tempo has a negative and significant effect with a regression coefficient β equal to a value of -39.4043 and a p-value equal to 0.0000. The type of brand also has a negative and significant effect with a regression coefficient β equal to a value of -20.9093 and a p-value equal to 0.0016. The interaction between the independent variable (musical tempo) and the moderator (brand type) is marginally significant, with a p-value equal to 0.0638.

Conditional effects of the focal predictor at values of the moderator

Type of brand	effect	se	t	p
0.0000	-39.4043	6.4622	-6.0976	0.0000
1.0000	-22.1458	6.6281	-3.3412	0.0010

Looking at the conditional effects of the focal predictor at values of the moderator, it can be interpreted that when the type of brand is **luxury** (luxury = 0), increasing musical tempo (from slow to fast) has a negative and significant effect on the third dependent variable (willingness to pay for a belt). Where the regression coefficient β is equal to a value of -39.4043 and a p-value equal to 0.0000. Furthermore, when the type of brand is **fast fashion** (fast fashion = 1), the effect of moving from a slow tempo to a faster tempo is negative and significant (p-value = 0.0010) and the regression coefficient β is equal to a value of -22.1458. For this reason, results suggest that it makes sense for luxury brands to adopt a slower tempo musical background, however, this result, although with a smaller effect, also applies to fast fashion brands.

Matrix 4

Outcome variable: Willingness to pay for a scarf

Model	coefficient	se	t	p
Constant	56.9804	4.8885	11.6561	0.0000
Musical tempo	-40.4004	6.9478	-5.8148	0.0000
Brand type	-26.2304	7.0205	-3.7362	0.0002
Interaction	23.6296	9.9526	2.3742	0.0186

A regression analysis was conducted using model 1 of the SPSS Process Macro extension Version 4.2 by Andrew F.Hayes. The independent variable X (musical tempo: slow versus fast) is of categorical nominal nature and, consequently, coded in two different conditions, where 0 (slow tempo) and 1 (fast tempo). The moderator W (brand type:

luxury versus fast fashion) is also of categorical nominal nature and, therefore, coded in two different conditions, where 0 (luxury brand) and 1 (fast fashion brand). On the other hand, the fourth dependent variable Y4 (willingness to pay for a scarf) is of continuous metric nature. From the table above it can be seen that musical tempo has a negative and significant effect with a regression coefficient β equal to a value of -40.4004 and a p-value equal to 0.0000. The type of brand also has a negative and significant effect with a regression coefficient β equal to a value of -26.2304 and a p-value equal to 0.0002. The interaction between the independent variable (musical tempo) and the moderator (brand type) is significant, with a p-value equal to 0.0186.

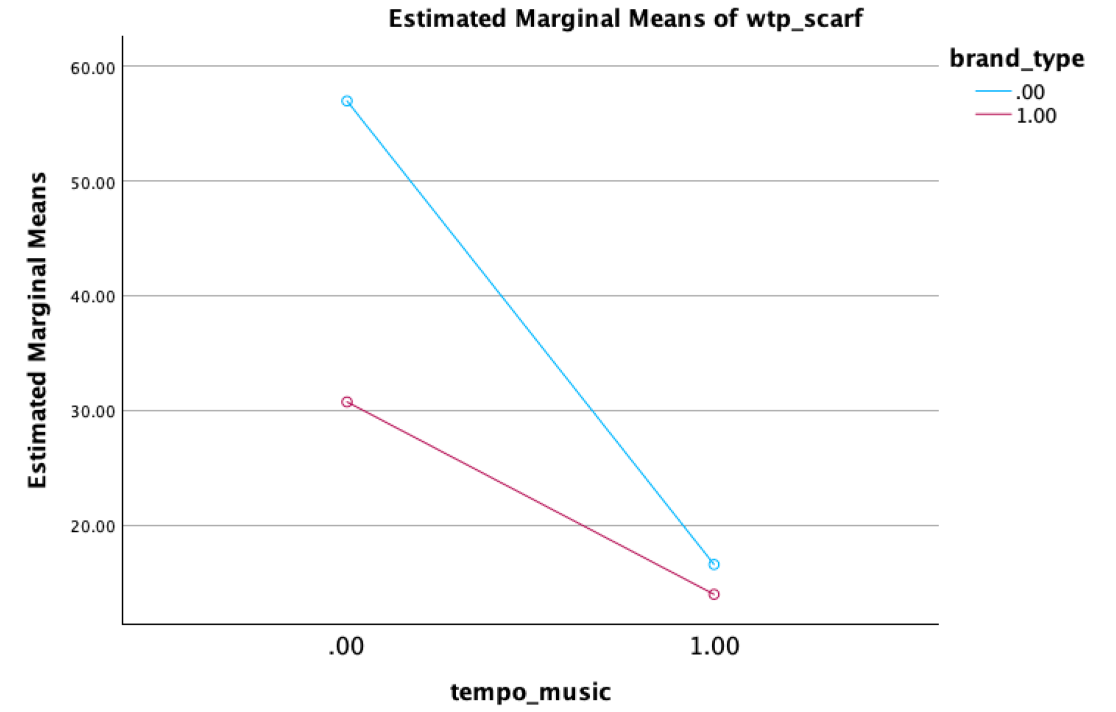
Conditional effects of the focal predictor at values of the moderator

Type of brand	effect	se	t	p
0.0000	-40.4004	6.9478	-5.8148	0.0000
1.0000	-16.7708	7.1261	-2.3534	0.0196

Looking at the conditional effects of the focal predictor at values of the moderator, it can be interpreted that when the type of brand is **luxury** (luxury = 0), increasing musical tempo (from slow to fast) has a negative and significant effect on the fourth dependent variable (willingness to pay for a scarf). Where the regression coefficient β is equal to a value of -40.4004 and a p-value equal to 0.0000. Furthermore, when the type of brand is **fast fashion** (fast fashion = 1), the effect of moving from a slow tempo to a faster tempo is negative and significant (p-value = 0.0196) and the regression coefficient β is equal to a value of -16.7708. For this reason, results suggest that it makes sense for luxury brands to adopt a slower tempo musical background. However, this result, although with a much smaller effect, also applies also to fast fashion brands.

A Two-Way ANOVA was conducted to obtain the interaction plot for the first dependent variable Y (brand liking) where the independent variable X (musical tempo: slow versus fast) is of categorical nominal nature and, consequently, coded in two different conditions, where 0 (slow tempo) and 1 (fast tempo). The moderator W (brand type: luxury versus fast fashion) where 0 = luxury brand and 1 = fast fashion brand, provided evidence for the luxury brand being more liked but only when slow tempo music was used.

Profile Plots



Matrix 5

Outcome variable: fit

Model	coefficient	se	t	p
Constant	6.2157	0.2202	28.2276	0.0000
Musical tempo	-2.7824	0.3130	-8.8904	0.0000
Brand type	-2.7087	0.3162	-8.5655	0.0000
Interaction	5.1504	0.4483	11.4885	0.0000

A regression analysis was conducted using model 7 (moderated mediation) of the SPSS Process Macro extension Version 4.2 by Andrew F.Hayes. The independent variable X (musical tempo: slow versus fast) is of categorical nominal nature and, consequently, coded in two different conditions, where 0 (slow tempo) and 1 (fast tempo). The moderator W (brand type: luxury versus fast fashion) is also of categorical nominal nature and, therefore, coded in two different conditions, where 0 (luxury brand) and 1 (fast fashion brand). The mediator variable M is the background between the music and the type of brand. This analysis was conducted on the first dependent variable Y1 (brand liking). This analysis was repeated for the other dependent variables. From the table above regarding the outcome variable: fit (the mediator), it can be seen that musical tempo has a negative and significant effect with a regression coefficient β equal to a value of -2.7824 and a p-value equal to 0.0000. The type of brand also has a negative and significant effect with a regression coefficient β equal to a value of -2.7087 and a p-value equal to 0.0000. The interaction between the independent variable (musical tempo) and the moderator (brand type) on the mediator (fit) is significant, with a p-value equal to 0.0000.

Conditional effects of the focal predictor at values of the moderator

Type of brand	effect	se	t	p
0.0000	-2.7824	0.3130	-8.8904	0.0000
1.0000	2.3681	0.3210	7.3773	0.0000

Looking at the conditional effects of the focal predictor at values of the moderator, it can be interpreted that when the type of brand is **luxury** (luxury = 0), increasing musical tempo (from slow to fast) has a negative and significant effect. Where the regression coefficient β is equal to a value of -2.7824 and a p-value equal to 0.0000. On the other hand, when the type of brand is **fast fashion** (fast fashion = 1), the effect of moving from a slow tempo to a faster tempo is positive and significant (p-value = 0.0000) and the regression coefficient β is equal to a value of 2.3681. For this reason, results suggest that it makes sense for luxury brands to adopt a slower tempo musical background and it makes sense for fast fashion brands to adopt a faster tempo musical background.

Outcome variable: brand liking

Model	coefficient	se	t	p
Constant	3.9505	0.2878	13.7257	0.0000
Musical tempo	-0.5012	0.2056	-2.4375	0.0157
Fit	0.2821	0.0508	5.5582	0.0000

From the table above, looking at the results for the outcome variable: brand liking, the effect of the mediator (fit between the background music and the type of brand) on the dependent variable Y1 (brand liking) has a positive effect and is significant. With a regression coefficient of β equal to 0.2821 and a p-value of 0.0000.

The index of moderated mediation presented a value of 1.4528 and is significant, thus, meaning that the type of brand successfully moderated this mediation confirming that the mediation took part in this relationship.

4.4 General discussion

4.4.1 Theoretical contributions

This experimental study contributes to existing literature by providing greater evidence regarding the impact of musical tempo manipulation on consumer attitudes towards brands. Specifically, this study confirms that varying the musical tempo of background music does indeed affect consumers' attitudes towards a brand. Furthermore, the type of brand effectively acts as a moderating variable. These findings add to previous literature exploring the relationship between music and consumer attitudes such as fast tempo music evoking greater feelings of energy and joy thus yielding greater consumer movement and flow in physical shops or slower tempo music providing a greater feeling of tranquillity and sophistication while encouraging greater spending. Nonetheless, this study adds to these findings by looking at how the type of fashion brand (whether luxury or fast fashion) also plays a role in influencing consumer responses. Furthermore, this study also looks at whether the fit between the background music and the type of brand acted as a mediator in this relationship.

Results provided evidence showing elements of support for all four hypotheses. This study confirmed existing research by Milliman (1982) and Caldwell et al., (1999) looking at musical tempo manipulations and their effects on consumers. In fact, this study proved that varying the musical tempo of background music does indeed impact consumers' attitudes towards a brand. Furthermore, the mediating role of the *fit between the background music and the type of brand* was successfully proven showing that a greater *fit* positively impacted consumer attitudes supporting previous literature by Doucé et al., (2022) showing that greater congruence between background music and online stores led to greater positive responses by consumers. This study also proved the moderating role of the *type of brand* supporting previous literature conducted by Kim et al., (2023) looking at the moderating role of type of fashion brand (whether sports or luxury) on the effect of background music speed on consumers.

4.4.2 Managerial implications

A series of managerial implications can be derived from this study. Musical tempo manipulation can be an important tool for brand managers, especially in the field of fashion, to develop and maximise the potential of their brands. In order to fully exploit the potential of this manipulation, it is important to keep in mind the identity and mission of a brand.

For this reason, the first managerial implication regards the fit between the background music and the type of brand. brand managers should always keep in mind what their brand wants to communicate and what it represents, this meaning that also the background music must effectively be in line with the message the brand wants to communicate. Hence, for an effective brand strategy using background music, there should be a promising fit between the background music and the type of brand as results have proven that a greater fit between the background music and the type of brand positively impacts consumer attitudes.

The second managerial implication regards the moderating role of the brand type. Results provided evidence supporting the idea that luxury brands should adopt a slower musical tempo as this has a positive effect on consumers. For this reason, marketing managers and brand managers of luxury brands wanting to exploit the full potential of their brand, should consider prioritising slower tempo music as part of their brand communication in order to maximise the effects on consumers. On the other hand, results for fast fashion brands show elements of support in terms of associating faster musical tempos to fast fashion brands. However, this is not always the case, in fact, results also provided evidence that slower tempo music had greater positive effects on consumers and, in another case, the difference between slow and fast tempo was not significant. For this reason, fast fashion brand managers are freer to select depending on their communication whether to use faster or slower tempo music.

The third managerial implication sheds light on the idea that music can be a powerful tool to develop marketing strategies. For this reason, marketing managers should highly take into consideration all factors (such as musical tempo variations) able to influence the perception of products. As, in fact, results have confirmed that varying the musical tempo of background music solicits different consumer responses.

4.4.3 Limitations and further research

The first limitation that needs to be addressed regards the sample size of the study. Although 197 respondents actively took part, this sample may not be large enough in order to provide reliable and definitive findings. Future research should focus on using a greater sample. Furthermore, the study took part in Italy, specifically, in Rome. Utilising one single country is not enough to provide empirical evidence for the findings. Future research should be conducted in more countries in order to obtain more trustworthy results. Additionally, although participant ages ranged between 18 years and 64 years of age, the sample was mainly composed of young people with an average age of 28.68 years. Therefore, future research should focus on targeting a greater age range with a higher average age. Another limitation regards the choice to use a convenience sample, thus forcing the selection of respondents with potentially similar backgrounds. In fact, many respondents were university students. Future research could address diversifying the sampling technique in order to obtain a diversified sample providing better representation for the population. Another limitation regards the selection of the musical tempo. This study diversified between the slow musical tempo performed at a speed of 95 BPM and the fast musical tempo performed at a speed of 120 BPM. This could have possibly been too little of a speed difference. Future research could address greater differences in musical tempo in order to fully perceive the manipulation of the independent variable. Finally, another limitation could address the type of background music used as a stimulus as for this study, only one genre was used. Different genres could be used to reduce the biasing effect of the type of genre on the type of brand as it could be the case that, besides the musical tempo, certain musical genres go better with certain types of brands than others.

Sitography

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<u>Appendices</u>

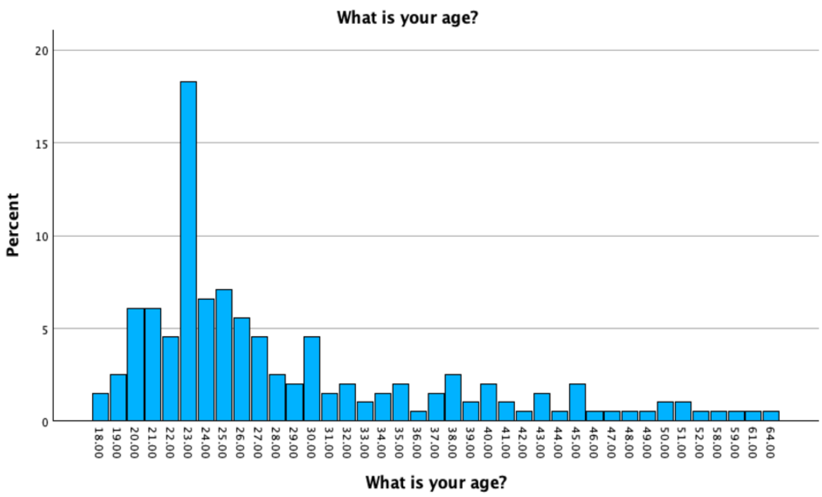
Appendix A – Descriptive statistics: age

Frequencies

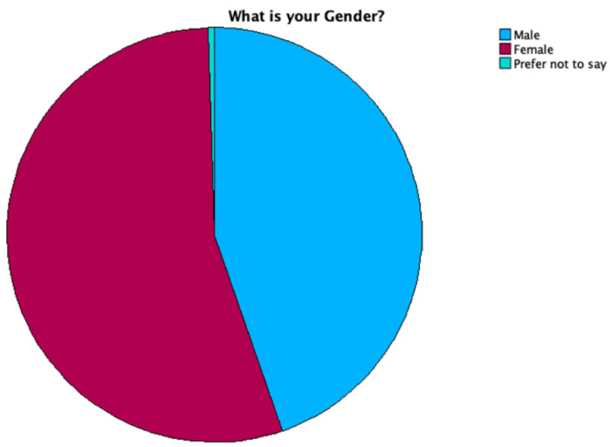
Statistics

What is your age?

N	Valid	197
	Missing	0
Mean		28.6853
Median		25.0000
Mode		23.00
Std. Deviation		9.22632
Variance		85.125
Range		46.00
Minimum		18.00
Maximum		64.00



Appendix B – Descriptive statistics: Gender



Frequencies

Statistics

What is your Gender?

N	Valid	197
	Missing	0
Mode		2

What is your Gender?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	88	44.7	44.7	44.7
	Female	108	54.8	54.8	99.5
	Prefer not to say	1	.5	.5	100.0
	Total	197	100.0	100.0	

Appendix C – Factor analysis

Correlation Matrix

		Now please think again of the logo and the background music of Hammond. Please indicate to what extent you agree or disagree with the following statements. - I think there is a fit between the brand Hammond and the background music	Now please think again of the logo and the background music of Hammond. Please indicate to what extent you agree or disagree with the following statements. - I think the background music is consistent with the brand Hammond	Now please think again of the logo and the background music of Hammond. Please indicate to what extent you agree or disagree with the following statements. - I think the background music is complementary to the brand Hammond
Correlation	Now please think again of the logo and the background music of Hammond. Please indicate to what extent you agree or disagree with the following statements. - I think there is a fit between the brand Hammond and the background music	1.000	.942	.888
	Now please think again of the logo and the background music of Hammond. Please indicate to what extent you agree or disagree with the following statements. - I think the background music is consistent with the brand Hammond	.942	1.000	.910
	Now please think again of the logo and the background music of Hammond. Please indicate to what extent you agree or disagree with the following statements. - I think the background music is complementary to the brand Hammond	.888	.910	1.000

Appendix D – KMO, Bartlett's test, Communalities table and Scree plot

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.764
Bartlett's Test of Sphericity	Approx. Chi-Square	828.539
	df	3
	Sig.	<.001

Communalities

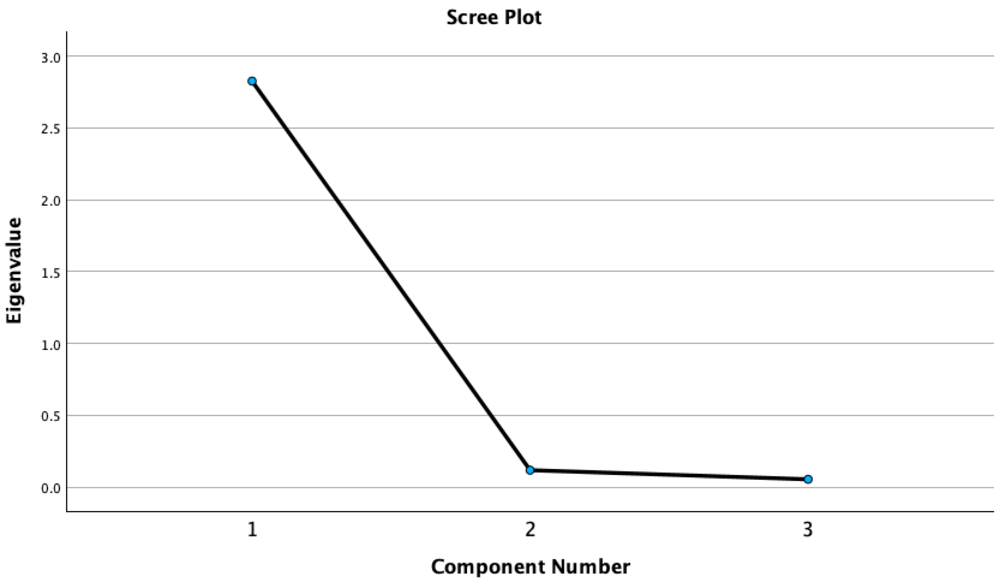
	Initial	Extraction
Now please think again of the logo and the background music of Hammond. Please indicate to what extent you agree or disagree with the following statements. - I think there is a fit between the brand Hammond and the background music	1.000	.945
Now please think again of the logo and the background music of Hammond. Please indicate to what extent you agree or disagree with the following statements. - I think the background music is consistent with the brand Hammond	1.000	.960
Now please think again of the logo and the background music of Hammond. Please indicate to what extent you agree or disagree with the following statements. - I think the background music is complementary to the brand Hammond	1.000	.922

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.827	94.230	94.230	2.827	94.230	94.230
2	.118	3.944	98.174			
3	.055	1.826	100.000			

Extraction Method: Principal Component Analysis.



Appendix E – Reliability test

Reliability

Scale: ALL VARIABLES

Case Processing Summary

		N	%
Cases	Valid	210	99.5
	Excluded[a]	1	.5
	Total	211	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.969	.969	3

Appendix F – Regression analysis model 1 and Two-Way ANOVA for the first dependent variable: brand liking

Matrix

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : brand_li
    X  : tempo_mu
    W  : brand_ty

Sample
Size:  197

**************************************************************************
OUTCOME VARIABLE:
 brand_li

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .2688      .0723     2.3198     5.0116     3.0000   193.0000      .0023

Model
              coeff         se          t          p       LLCI       ULCI
constant     5.7451      .2133    26.9378      .0000     5.3245     6.1657
tempo_mu    -1.0651      .3031    -3.5138      .0006    -1.6629     -.4672
brand_ty     -.8493      .3063    -2.7727      .0061    -1.4534     -.2452
Int_1        1.0026      .4342     2.3090      .0220      .1462     1.8590

Product terms key:
 Int_1    :        tempo_mu x        brand_ty

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0256     5.3316     1.0000   193.0000      .0220
----------
    Focal predict: tempo_mu (X)
          Mod var: brand_ty (W)

Conditional effects of the focal predictor at values of the moderator(s):

   brand_ty     Effect         se          t          p       LLCI       ULCI
      .0000    -1.0651      .3031    -3.5138      .0006    -1.6629     -.4672
     1.0000     -.0625      .3109     -.2010      .8409     -.6757      .5507

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

Page 1

Univariate Analysis of Variance

Between-Subjects Factors

		N
tempo_music	.00	99
	1.00	98
brand_type	.00	101
	1.00	96

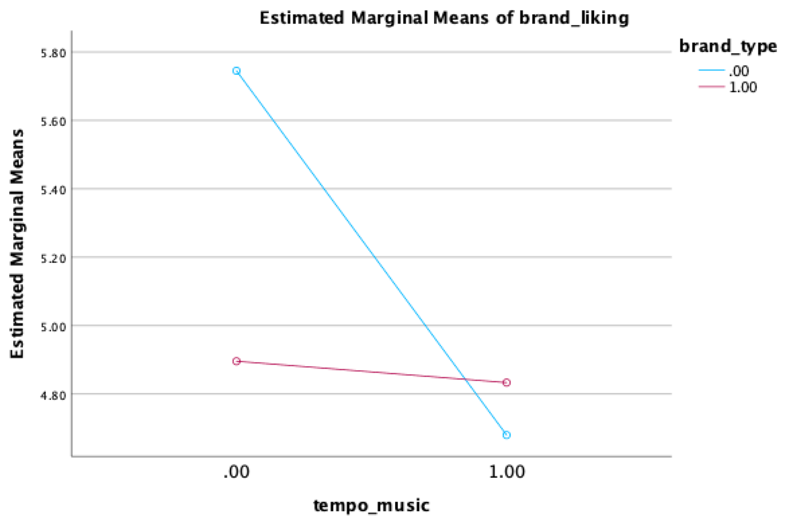
Tests of Between-Subjects Effects

Dependent Variable: brand_liking

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	34.877[a]	3	11.626	5.012	.002
Intercept	4997.808	1	4997.808	2154.458	<.001
tempo_music	15.644	1	15.644	6.744	.010
brand_type	5.959	1	5.959	2.569	.111
tempo_music * brand_type	12.368	1	12.368	5.332	.022
Error	447.712	193	2.320		
Total	5498.000	197			
Corrected Total	482.589	196			

a. R Squared = ,072 (Adjusted R Squared = ,058)

Profile Plots



Appendix G – Regression analysis model 1 and Two-Way ANOVA for the second dependent variable: willingness to visit the Instagram page

Matrix

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : wtv_inst
    X  : tempo_mu
    W  : brand_ty

Sample
Size:  197

**************************************************************************
OUTCOME VARIABLE:
 wtv_inst

Model Summary
         R       R-sq        MSE          F        df1        df2          p
     .2036      .0415     2.4342     2.7833     3.0000   193.0000      .0421

Model
              coeff         se          t          p       LLCI       ULCI
constant     5.6863      .2185    26.0275      .0000     5.2554     6.1172
tempo_mu     -.7663      .3105    -2.4678      .0145    -1.3787     -.1539
brand_ty     -.5196      .3138    -1.6561      .0993    -1.1384      .0992
Int_1         .4954      .4448     1.1139      .2667     -.3818     1.3727

Product terms key:
 Int_1    :        tempo_mu x        brand_ty

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0062     1.2407     1.0000   193.0000      .2667

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

Univariate Analysis of Variance

Between-Subjects Factors

		N
tempo_music	.00	99
	1.00	98
brand_type	.00	101
	1.00	96

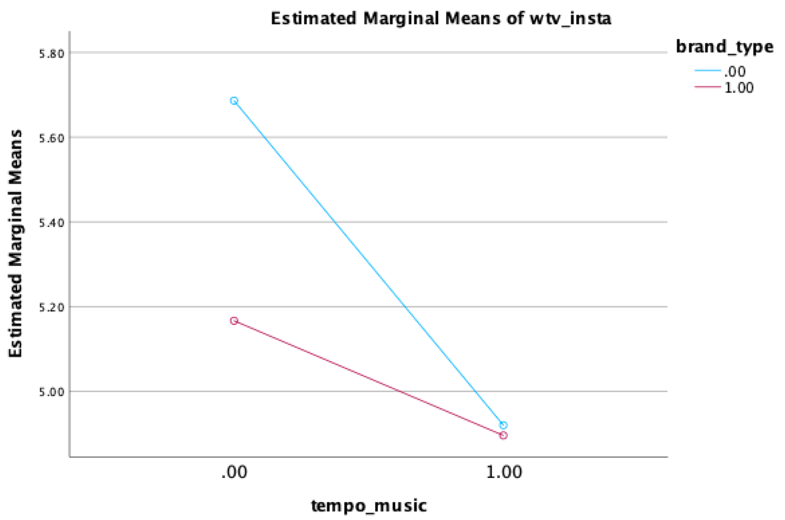
Tests of Between-Subjects Effects

Dependent Variable: wtv_insta

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	20.326[a]	3	6.775	2.783	.042
Intercept	5256.239	1	5256.239	2159.303	<.001
tempo_music	13.234	1	13.234	5.437	.021
brand_type	3.638	1	3.638	1.495	.223
tempo_music * brand_type	3.020	1	3.020	1.241	.267
Error	469.806	193	2.434		
Total	5761.000	197			
Corrected Total	490.132	196			

a. R Squared = ,041 (Adjusted R Squared = ,027)

Profile Plots



Appendix H – Regression analysis model 1 and Two-Way ANOVA for the third dependent variable: willingness to pay for a belt

Matrix

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : wtp_belt
    X  : tempo_mu
    W  : brand_ty

Sample
Size:  197

**************************************************************************
OUTCOME VARIABLE:
 wtp_belt

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4730      .2237  1054.3479    18.5366     3.0000   193.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant    58.7843     4.5468    12.9287      .0000    49.8165    67.7521
tempo_mu   -39.4043     6.4622    -6.0976      .0000   -52.1500   -26.6586
brand_ty   -20.9093     6.5299    -3.2021      .0016   -33.7884    -8.0303
Int_1       17.2585     9.2570     1.8644      .0638     -.9994    35.5163

Product terms key:
 Int_1    :        tempo_mu x        brand_ty

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0140     3.4759     1.0000   193.0000      .0638
----------
    Focal predict: tempo_mu (X)
          Mod var: brand_ty (W)

Conditional effects of the focal predictor at values of the moderator(s):

   brand_ty     Effect         se          t          p       LLCI       ULCI
      .0000   -39.4043     6.4622    -6.0976      .0000   -52.1500   -26.6586
     1.0000   -22.1458     6.6281    -3.3412      .0010   -35.2186    -9.0731

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

Univariate Analysis of Variance

Between-Subjects Factors

		N
tempo_music	.00	99
	1.00	98
brand_type	.00	101
	1.00	96

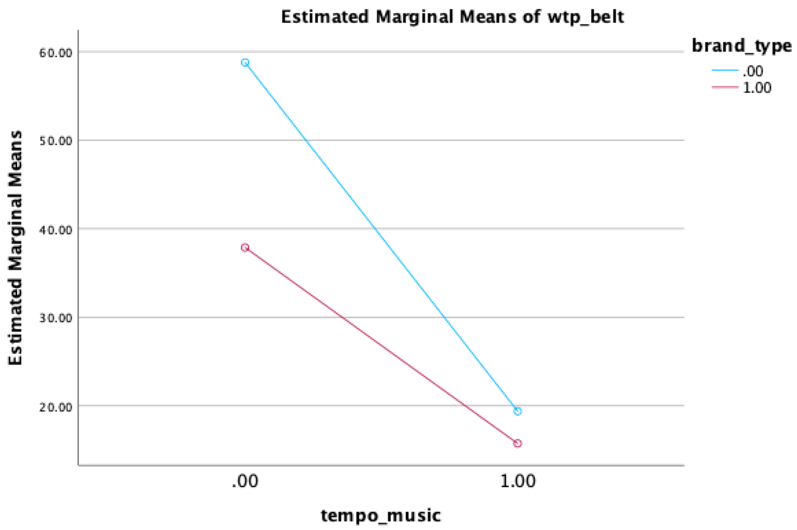
Tests of Between-Subjects Effects

Dependent Variable: wtp_belt

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	58632.143[a]	3	19544.048	18.537	<.001
Intercept	213633.185	1	213633.185	202.621	<.001
tempo_music	46612.654	1	46612.654	44.210	<.001
brand_type	7421.771	1	7421.771	7.039	.009
tempo_music * brand_type	3664.804	1	3664.804	3.476	.064
Error	203489.137	193	1054.348		
Total	479236.000	197			
Corrected Total	262121.279	196			

a. R Squared = ,224 (Adjusted R Squared = ,212)

Profile Plots



Appendix I – Regression analysis model 1 and Two-Way ANOVA for the fourth dependent variable: willingness to pay for a scarf

Matrix

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 1
    Y  : wtp_scar
    X  : tempo_mu
    W  : brand_ty

Sample
Size:  197

**************************************************************************
OUTCOME VARIABLE:
 wtp_scar

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4462      .1991  1218.7520    15.9926     3.0000   193.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant    56.9804     4.8885    11.6561      .0000    47.3387    66.6221
tempo_mu   -40.4004     6.9478    -5.8148      .0000   -54.1038   -26.6970
brand_ty   -26.2304     7.0205    -3.7362      .0002   -40.0772   -12.3836
Int_1       23.6296     9.9526     2.3742      .0186     3.9998    43.2593

Product terms key:
 Int_1    :        tempo_mu x        brand_ty

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .0234     5.6369     1.0000   193.0000      .0186
----------
    Focal predict: tempo_mu (X)
          Mod var: brand_ty (W)

Conditional effects of the focal predictor at values of the moderator(s):

   brand_ty     Effect         se          t          p       LLCI       ULCI
      .0000   -40.4004     6.9478    -5.8148      .0000   -54.1038   -26.6970
     1.0000   -16.7708     7.1261    -2.3534      .0196   -30.8259    -2.7158

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

WARNING: Variables names longer than eight characters can produce incorrect output
when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```

Univariate Analysis of Variance

Between-Subjects Factors

		N
tempo_music	.00	99
	1.00	98
brand_type	.00	101
	1.00	96

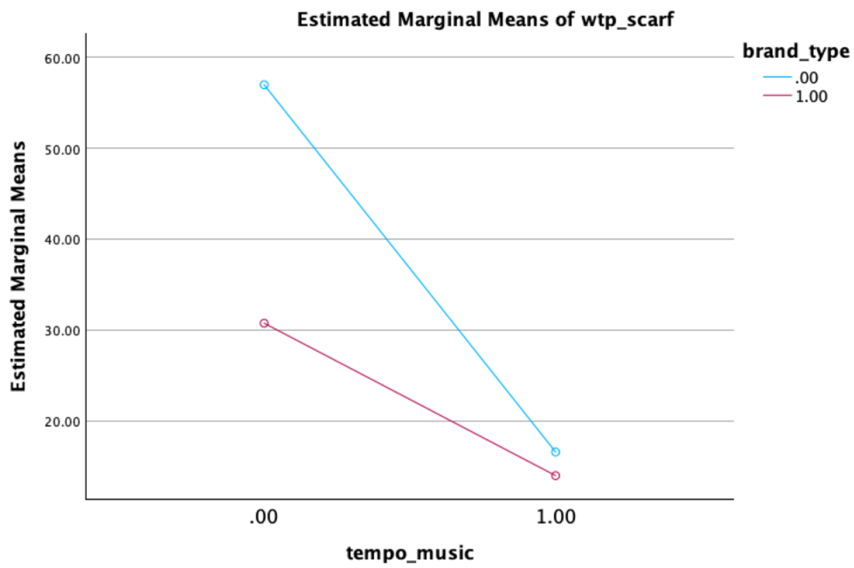
Tests of Between-Subjects Effects

Dependent Variable: wtp_scarf

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	58472.881[a]	3	19490.960	15.993	<.001
Intercept	172162.462	1	172162.462	141.261	<.001
tempo_music	40216.164	1	40216.164	32.998	<.001
brand_type	10227.556	1	10227.556	8.392	.004
tempo_music * brand_type	6870.002	1	6870.002	5.637	.019
Error	235219.140	193	1218.752		
Total	469316.000	197			
Corrected Total	293692.020	196			

a. R Squared = ,199 (Adjusted R Squared = ,187)

Profile Plots



Appendix J – Regression analysis model 7 tested on the first dependent variable: brand liking

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : 7
    Y  : brand_li
    X  : tempo_mu
    M  : fit
    W  : brand_ty

Sample
Size:  197

**************************************************************************
OUTCOME VARIABLE:
 fit

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .6400      .4096     2.4729    44.6318     3.0000   193.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     6.2157      .2202    28.2276      .0000     5.7814     6.6500
tempo_mu    -2.7824      .3130    -8.8904      .0000    -3.3996    -2.1651
brand_ty    -2.7087      .3162    -8.5655      .0000    -3.3325    -2.0850
Int_1        5.1504      .4483    11.4885      .0000     4.2662     6.0346

Product terms key:
 Int_1    :        tempo_mu x        brand_ty

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      .4038   131.9859     1.0000   193.0000      .0000
----------
    Focal predict: tempo_mu (X)
          Mod var: brand_ty (W)

Conditional effects of the focal predictor at values of the moderator(s):

   brand_ty     Effect         se          t          p       LLCI       ULCI
      .0000    -2.7824      .3130    -8.8904      .0000    -3.3996    -2.1651
     1.0000     2.3681      .3210     7.3773      .0000     1.7350     3.0012

**************************************************************************
OUTCOME VARIABLE:
 brand_li

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .4084      .1668     2.0726    19.4188     2.0000   194.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
```

Page 1

```
constant     3.9505      .2878    13.7257      .0000     3.3828     4.5181
tempo_mu     -.5012      .2056    -2.4375      .0157     -.9067     -.0957
fit           .2821      .0508     5.5582      .0000      .1820      .3822

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
     -.5012      .2056    -2.4375      .0157     -.9067     -.0957

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 tempo_mu    ->    fit         ->    brand_li

   brand_ty     Effect     BootSE   BootLLCI   BootULCI
      .0000     -.7849      .1668    -1.1341     -.4636
     1.0000      .6680      .1661      .3680     1.0168

Index of moderated mediation (difference between conditional indirect effects):
              Index     BootSE   BootLLCI   BootULCI
brand_ty     1.4528      .3064      .8610     2.0871

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

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when some variables in the data file have the same first eight characters. Shorter
variable names are recommended. By using this output, you are accepting all risk
and consequences of interpreting or reporting results that may be incorrect.

------ END MATRIX -----
```